The Real Effects of Banking Crises

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Philipp Schaz, M.Sc.

Präsidentin der Humboldt-Universität zu Berlin:
Prof. Dr.-Ing. Dr. Sabine Kunst

Dekan der Wirtschaftswissenschaftlichen Fakultät:
Prof. Dr. Daniel Klapper

Gutachter:
1. Prof. Marcel Fratzscher, Ph.D.
2. Prof. Dr. Joachim Gassen

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To Anja.

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Abstract

This thesis investigates the effect of banking crises on real economic outcomes in three independent chapters. In chapter one, I classify a large sample of banks according to the geographic diversification of their international syndicated loan portfolio. Results show that diversified banks maintain higher loan supply during banking crises in borrower countries. The positive loan supply effects lead to higher investment and employment growth for firms. Further distinguishing banks by nationality reveals a pecking order: diversified domestic banks are the most stable source of funding, while foreign banks with little diversification are the most fickle. In chapter two, I show that banks' industry specialization determines how banks transmit funding shocks during banking crises to borrowers and how they spill over to non-crisis countries. Results show that banks insulate their main industries from the banking crisis while they reduce lending most to their non-main industries. Moreover, I provide evidence on spillover effects, as banks hit by a banking crisis in one borrower country reduce lending to firms in non-crisis countries. However, this contagion effect is significantly weaker for firms in banks' main industries. In chapter three, I examine the effects of government support for European banks, such as recapitalizations on financial integration and firm outcomes. Results show that bailout banks increase their home bias in lending by a quarter more than non-bailout banks. In turn, the negative loan supply effect on foreign firms translates into lower sales and employment growth. In the home market, government support distorts credit allocation by shifting lending to larger, safer and less innovative firms. Moreover, I document that politicians gain influence over banks by transferring control rights to the government as part of the support scheme.

Diese Dissertation untersucht die Auswirkungen von Bankenkrisen auf die Realwirtschaft in drei unabhängigen Kapiteln. Kapitel 1 klassifiziert die geografische Diversifikation einer Großzahl von Banken, anhand deren international syndizierten Kreditportfolios. Ergebnisse zeigen ein höheres Kreditangebot durch diversifizierte Banken während Bankenkrisen die sich in Kreditnehmerländern ereignen. Dieses relativ stabilere Kreditangebot führt zu höherem Investitions- und Beschäftigungswachstum von Unternehmen. Eine weiterführende Unterteilung von Banken anhand derer Nationalität zeigt eine Rangfolge auf: diversifizierte inländische Banken erweisen sich als die stabilste und ausländische Banken mit geringer Diversifikation als die instabilste Finanzierungsquelle. In Kapitel 2 analysiere ich die Rolle der industriellen Spezialisierung von Banken in der Transmission von Finanzierungsshocks. Anhand der Ergebnisse schützen Banken Unternehmen die Teil ihrer spezialisierten Industrien sind vor der Bankenkrise und reduzieren ihre Kreditvergabe hingegen am stärksten an Industrien, in welchen sie weniger spezialisiert sind. Darüber hinaus finde ich Evidenz für Übertragungseffekte durch reduzierte Kreditvergabe auch in Nicht-Krisenländern. Dieser Übertragungseffekt ist jedoch gedämpft für Unternehmen aus spezialisierten Industrien. Kapitel 3 untersucht die Effekte von Bankenrettungen in Europa auf die globalen Kreditströme. Gerettete Banken weisen einen höheren Anstieg des Anteils an inländischen Unternehmen in der Kreditvergabe auf als nicht-gerettete Banken. Das negative Kreditangebot für ausländische Unternehmen führt zu einer Verringerung des Absatz- und Beschäftigungswachstums. Im inländischen Markt hingegen führt die Bankenrettung zu einer Verzerrung der Kreditallokation, hin zu größeren und weniger innovativen Unternehmen. Darüber hinaus dokumentiere ich eine stärkere politische Einflussnahme, da Kontrollrechte im Zuge der Bankenrettung an die Regierung übertragen werden.

Introduction

The collapse of Lehman Brothers in 2008 has raised concerns about the threat of financial instability to the greater economy. But does bank health affect economic outcomes at firms? This question has sparked substantial interest by policy makers and academics, while the public debate has been ignited by the deeply unpopular government support for banks during the Great Financial Crisis. In spite of the attempts to stabilize the financial sector, banks reduced lending to firms, and countries worldwide saw a sharp decline in economic growth and employment in the wake of the crisis.

This thesis investigates the effect of banking crises on real economic outcomes. Essentially, I examine the transmission of crises operating through the bank lending channel. Banking crises lead to funding shocks for banks who, in turn, transmit this shock to borrowing firms through a reduction in loan supply. This lending reduction amplifies financial constraints, which forces firms to adapt their business strategy and, thus, translating into real effects to the economy. However, the lending response to the crisis varies substantially across countries and banks, depending on banks' access to funding, business model, exposure to the crisis or the availability of government support. It is therefore a key objective for policy makers and academics to better understand the determinants of this transmission in order to improve the resilience of the economy to financial shocks.

In three chapters, I investigate the role of banks' business models and the political economy setting in the transmission of banking crises. The first two chapters examine the effects of banks' portfolio concentration by geography and industry on loan supply during crises. The third chapter examines the role of moral suasion by governments on crisis transmission through banks receiving government support.

In chapter one, I classify a large sample of banks according to the geographic diversification of their international syndicated loan portfolio. The results show that diversified banks maintain higher loan supply during banking crises in borrower countries. The positive loan supply effects lead to higher investment and employment growth for firms. Diversified banks are stabilizing due to their ability to raise additional funding during times of distress, which also shields connected markets from spillovers. Further distinguishing banks by nationality reveals a pecking order: diversified domestic banks are the most stable source of funding, while foreign banks with little diversification are the most fickle. The findings suggest that the decline in financial integration since the recent crisis increases countries' vulnerability to local shocks.

In chapter two, I show that banks' industry specialization determines how banks transmit funding shocks during banking crises to borrowers and how they spill over to non-crisis countries. Using detailed bank-firm level data on cross-country syndicated loans, I show that banks insulate their main industries from the banking crisis while they reduce lending most to their non-main industries. I document a positive relationship between bank specialization and firm lending: Banks reduce lending strongest to firms from their least specialized industries. Moreover, I find that banks protect their specialized industries on aggregate, rather than cherry-pick firms within a specialized industry they know well. When I look at industry level real effects, I find that increasing an industry's exposure to specialized banks by one standard deviation, undoes the negative effect of the crisis on industry-wide employment. To analyze spillover effects, I investigate how banking crises are transmitted through cross-border bank lending to non-crisis countries. I provide evidence on spillover effects, as banks hit by a banking crisis in one borrower country reduce lending to firms in non-crisis countries. However, this contagion effect is significantly weaker for firms in banks' main industries. I show that results are not driven by bank characteristics, firm quality, or bank-firm specific information that banks collected through previous interactions. The findings suggest that bank industry specialization plays a crucial role in the transmission of financial shocks within and across countries.

In chapter three, I examine the effect of government support for banks, such as recapitalizations on financial integration and firm outcomes. Using data on European syndicated lending, results show that bailout banks increase their home bias in lending by a quarter more than non-bailout banks. In turn, discriminated foreign firms can only imperfectly substitute this fall in lending by switching banks or issuing corporate bonds. Thus, the negative loan supply effect translates into lower sales and employment growth for foreign firms. In addition, government support distorts credit allocation in the home market by shifting lending to larger, safer and less innovative firms. Moreover, I document that politicians gain influence over banks by transferring control rights to the government as part of the support scheme. These results suggest that locating bank resolution within the European Banking Union at the national level discourages international economic activity, distorts credit towards less productive firms and harms growth.

Chapter I

Bank Loan Supply during Crises: The Importance of Geographic Diversification

Based on Doerr and Schaz (2019).

1 Introduction

The last decades saw a steady increase in the importance of globally active banks. Banking integration peaked around 2007, but declined sharply during the global financial crisis. It has become a key objective for policy makers and academics to better understand the effects of integrated banks on financial stability and the real economy (BCBS, 2013). Several papers provide valuable evidence on the costs and benefits of lending by foreign banks.[1] However, an analysis of the consequences of banks' portfolio diversification on financial stability is largely absent from the literature.

In this paper we provide first cross-country evidence on how internationally diversified banks adjust lending during banking crises in their borrower countries. We find that diversified banks stabilize loan supply and smooth shocks. On the loan level, their loan supply during crises is 3.9 % higher, compared to banks with a concentrated portfolio. Higher loan supply has significant real effects on firm performance. Firms at the 75^{th}

[1] For theoretical papers highlighting the importance of banks' diversification and intra-bank capital markets, see Morgan, Rime and Strahan (2004), Cetorelli and Goldberg (2011, 2012), Kalemli-Ozcan, Papaioannou and Perri (2013a), Kalemli-Ozcan, Papaioannou and Peydró (2013b). For empirical evidence on the internal capital market, see De Haas and Van Lelyveld (2010); De Haas and van Lelyveld (2014), Buch and Goldberg (2014), Kerl and Niepmann (2015), Fillat, Garetto and Götz (2015), and Gilje, Loutskina and Strahan (2016). Claessens (2017) provides an excellent summary on cross-border lending.

percentile in terms of loan exposure to diversified banks have 1.5 % higher loan growth during banking crises, relative to firms at the 25^{th} percentile. This translates into stronger investment (4.6 %) and employment (1.1 %) growth. As detailed loan-level data allow us to rigorously control for credit demand effects, the positive effects of diversification reflect banks' loan supply. We also find that the positive loan supply effects of diversified banks are persistent. In the aftermath of a banking crisis, there is a permanent shift towards lending by diversified banks within and across firms.

To measure the degree of portfolio diversification of globally integrated banks, we use disaggregated data on worldwide syndicated lending. For each bank we construct a Herfindahl-Hirschman Index of the geographic diversification of its international loan portfolio, aggregated to the parent bank level. Banks with low portfolio concentration, i.e. those that lend to multiple countries, are classified as diversified. Our classification of banks builds on recent literature on banking integration that shows that geographically diversified banks have lower risk in their portfolio and cheaper access to funding during crises (Bord, Ivashina and Taliaferro, 2018; Levine, Lin and Xie, 2019). They use their internal capital markets to reallocate funds towards regions with high loan demand, thereby smoothing local economic shocks (Gilje, Loutskina and Strahan, 2016; Cortés and Strahan, 2017).[2] Our measure reflects the positive effects of diversification on obtaining and reallocating funds.

We provide evidence that geographically diversified banks are stabilizing due to their ability to raise new funds during times of distress. If banks are financially unconstrained when hit by a local financial shock, they can raise and distribute new funds to sustain loan supply in affected areas, but also connected non-crisis countries. Banks that face financial constraints must trade off where to allocate existing funds, similar to Stein (1997). Local shocks will then have spillover effects on connected countries. For example, during a banking crisis in Canada unconstrained banks can maintain lending in Canada and Mexico, while constrained banks cut lending in both countries. We show that, for highly diversified banks, maintaining loan growth in a crisis country has no spillover effects on unaffected non-crisis, countries that borrow from the same bank. However, for banks with a concentrated portfolio loan growth also falls in connected, but unaffected

[2] Gilje, Loutskina and Strahan (2016) show that banks distribute windfall profits through their branch network, Cortés and Strahan (2017) find that banks use internal capital markets to reallocate funds towards regions with high loan demand. As in our setting, reallocation has negative effects on connected areas of smaller and less diversified banks that cannot raise new funds. Bord, Ivashina and Taliaferro (2018) provide additional evidence that large and healthy banks raise new deposits to smooth shocks. Our measure reflects that diversified banks have better access to funds during distress and allocate them through their intra-bank market.

borrower countries. We interpret this as evidence that diversified banks have looser 'financial constraints' and can raise and distribute new funds to sustain loan supply. Non-diversified banks are financially constrained and must cut back lending in affected and unaffected areas when faced with a shock. To provide additional direct evidence on banks' liabilities, we further match a subsample of US banks with Federal Deposit Insurance Corporation (FDIC) data on depository institutions. In line with the hypothesis that diversified banks have better access to funding, we find that they raise new deposits at home during banking crises in borrower countries.

We contrast our categorization by diversification with the common classification in the literature by nationality into foreign and domestic banks. Diversified banks can be foreign or domestic, and foreign banks diversified or non-diversified. We find that classifying banks by diversification instead of nationality uncovers strikingly different behavior. While diversified banks stabilize loan supply during banking crises in host markets, foreign banks reduce their loan supply, relative to domestic banks. Our results reveal the following pecking order: diversified domestic banks are the most stable source of funding, while foreign banks with little diversification are the most fickle. Foreign, but diversified banks occupy an intermediate position between both extremes. The ordering speaks to findings on the flight home effect (Giannetti and Laeven, 2012) and behavior of gross capital flows during crises (Broner, Didier, Erce and Schmukler, 2013).

For robustness, we address alternative explanations to the argument that diversified banks smooth local shocks through better access to funding. We show that diversified banks have lower portfolio risk in terms of volatility of borrower sales growth. While a less risky portfolio could explain banks' stabilizing effect, we show that the positive effect of diversification remains stable once we control for portfolio risk. We then rule out possibility that diversified banks extend a lower share of their total loans to countries in crisis. Including the share of loans in crisis shows that, if anything, diversification becomes more important when a larger share of loans is in distress. To further probe the robustness of our results, we create an alternative measure of diversification that captures banks' international orientation. We group banks by the share of loans extended to foreign borrowers. Banks with a high share of international loans are categorized as 'international', those with primarily domestic loans as 'national'.[3] Our two classifications are complementary and positively correlated, but capture different dimensions of banking integration. We find that international banks are weakly stabilizing during host shocks.

[3]To exemplify the difference, think of a German bank that lends only to French firms. Under the alternative metric (international portfolio) it is highly international, while in our baseline (diversification) it is not.

However, once we include banks' diversification in the regression, the effect on international banks turns insignificant. Instead, we still find that diversification is the relevant factor for positive effects on loan supply. Similarly, we test geographic diversification against an alternative measure of diversification according to banks diversification across industries. We find that lending by geographically diversified banks cannot be explained by bank diversification across industries.[4] We also ensure that bank size is not driving our results. Further, findings are robust to excluding the global financial crisis, controlling for correlated regional crises affecting several countries at once, or contemporaneous shocks to home markets.

The key identification issue for cross-country studies using aggregate data is to control for loan demand. If diversified banks lend to different firms than banks with a concentrated portfolio, any observed differential change in loan volume reflects both demand and supply effects. Disaggregated data allow us to overcome this challenge. Our loan level analysis employs firm*bank and firm*time fixed effects to absorb all time-varying unobservable firm fundamentals.[5] The combination of both fixed effects allows shocks to affect each firm at each point in time heterogeneously and accounts for any change in loan demand.[6] For example, time-varying fixed effects on the firm level absorb changes in firm sales, management, or productivity, while bank*firm fixed effects control for distance between borrowers and lenders. On the firm level, we combine firm with country*industry*time fixed effects to control for time-varying industry demand. The identifying assumption is that loan demand by all firms within the same industry and country changes equally. While in principle firm demand could exhibit heterogeneity within industries, we run loan level regressions to confirm that this is of second order importance. The positive effect of diversification on credit hence reflects loan supply factors.

Our paper contributes to the literature in three ways. First, and to the best of our knowledge, we propose the first cross-country bank-level measure for banks' portfolio integration into the global financial system. Due to data limitations, so far most studies

[4]Boskovic, Doerr and Schaz (2019) provide evidence that bank lending during crises is more stable for those industries in which banks have an informational advantage through lending specialization to this industry.

[5]See Khwaja and Mian (2008); Jiménez, Atif, Peydro and Saurina Salas (2012); Jiménez, Ongena, Peydró and Saurina (2014); Morais, Peydro and Ruiz Ortega (2019).

[6]A related problem is self-selection that arises if, for example, the best firms would pair with diversified banks. To overcome this potential selection bias, we repeat our analysis on the restricted sample of firms that borrowed from both diversified and concentrated banks in each year (Khwaja and Mian, 2008). Coefficients for the reduced sample have the same sign and are of similar magnitude as for the full sample.

distinguish banks by headquarter location into foreign and domestic and look at cross-border lending.[7] While bank nationality has been shown to be an important determinant of loan supply, our approach captures the related, but distinct dimension of banks' integration into the financial system, captured by their portfolio allocation. This allows us to shed new light on banks' role during crises. Note that both categorizations need not be mutually exclusive. Diversified banks can be foreign, but domestic banks also diversified, depending on the country in which the shock originates. We find that grouping banks by diversification instead of nationality uncovers new patterns that complement existing findings in the literature on banking integration. It also helps reconcile conflicting findings on the effects of foreign banks during crises. The global scope of our detailed loan-level data allows for clean identification, as well as external validity.

Second, we contribute to the growing literature that analyzes the real effects of financial shocks and highlights the relevance of syndicated lending for firm performance.[8] Our results show that the effects of banking crises are heterogeneous across bank types and that firms' composition of lenders matters. The negative effects we find on the firm level suggest that firms cannot fully substitute syndicated loans across banks. If firms could fully replace syndicated loans by non-integrated banks with loans by diversified banks, exposure to either type would not affect loan growth differentially. However, while substitution is imperfect, we show that in the years following a banking crisis there is a persistent shift towards lending by diversified banks. Both within firms and within industries, the share of loans extended by diversified banks increases. Geographic diversification allows banks to capture a larger share of the market when their local competitors have to contract lending. Viewed from a different angle, this also implies that banking crises persistently alter the composition of lenders.

Finally, while the effect of shocks to banks' home markets and consequent spillovers are well explored, few papers investigate the role of banks during distress in their host markets.[9] Many crises over the last two decades were shocks to borrower countries and globally integrated banks were usually heavily involved. During the Asian crisis, Japanese and European banks were exposed to markets in Thailand, the Philippines, or South Korea; and during Argentina's woes, American banks had a strong presence in

[7] See, for example, Peek and Rosengren (1997, 2000); Cetorelli and Goldberg (2011, 2012); Schnabl (2012); Correa, Sapriza and Zlate (2013); De Haas and Van Horen (2013); De Haas and van Lelyveld (2014); Ongena, Peydró and Van Horen (2015); Bremus and Neugebauer (2018a).

[8] See Giannetti and Laeven (2012); Correa, Sapriza and Zlate (2013); De Haas and Van Horen (2013); Hale, Kapan and Minoiu (2016); Jiménez, Atif, Peydro and Saurina Salas (2012); Popov and Van Horen (2015); Morais, Peydro and Ruiz Ortega (2019).

[9] For an exception, see De Haas and Van Lelyveld (2006).

Latin America. As bank lending is a major source of firm financing, it is important to understand how banks react to host country shocks. So far, the discussion has mainly highlighted the costs and benefits of cross-border banking and how foreign banks spread home market shocks to connected markets (Claessens, 2017).

Our results contribute to the discussion on retrenchment in financial integration since the global financial crisis (Milesi-Ferretti and Tille, 2011; Claessens and Van Horen, 2015). Since the financial crisis, there has been a significant decline in cross-border banking and financial integration.[10] In addition, we show that banks' portfolio diversification declined. The verdict on whether this is good or bad for financial stability is still out. While some studies find that foreign banks adversely affect economic conditions in host markets, our results show that integrated banks with a diversified portfolio smooth financial shocks. Presence in several markets reduces banks' exposure to local shocks and gives them better access to new funds, which they can allocate towards countries in distress. This not only stabilizes lending in affected countries, but also mitigates contagions. In light of our results the recent decline in global banking is worrisome, as weaker integration into the global financial system, and hence less portfolio diversification, has detrimental effects on stability in host markets.

The remainder of the paper proceeds as follows. Section 2 discusses data and empirical strategy, Section 3 presents our main results. In Section 4 we check the robustness of our findings to alternative explanations, Section 5 provides extensions and additional robustness checks. Section 6 concludes.

2 Data & Empirical Strategy

This section describes data and construction of main variables. We then discuss the empirical strategy to identify changes in loan supply by banks during borrower-country banking crises, as well as their real effects on firms.

2.1 Geographic Diversification

We categorize banks according to the geographic diversification of their international syndicated loan portfolio. Building on recent literature, we argue that diversification allows banks to access cheaper funding, which they allocate towards borrower countries in crisis (Gilje, Loutskina and Strahan, 2016; Cortés and Strahan, 2017; Levine, Lin

[10] See also Cerutti and Claessens (2016); Bremus and Fratzscher (2015); Bussière, Schmidt and Valla (2018); Emter, Schmitz and Tirpák (2016); European Central Bank (2017); Acharya and Steffen (2015); Rose and Wieladek (2014).

and Xie, 2019). The mechanism is especially important during episodes of financial turmoil (Bord, Ivashina and Taliaferro, 2018). For each bank we construct a Herfindahl-Hirschman Index (HHI), based on the share of outstanding loans to each borrower country in each year. The index reflects the geographic dispersion of banks' loan portfolios across multiple countries. Based on the HHI, we then define *diversification (DIV)* for bank b in year t as

$$DIV_{b,t} = 1 - \sum_{j=1}^{J^b} s_{b,j,t}^2 \quad \in [0, \frac{J^b - 1}{J^b}], \tag{1}$$

where $s_{b,j,t}$ measures the share of a bank b's outstanding loans to borrowers in country j relative to its total outstanding loans in year t. Each bank is active in J^b distinct countries, i.e. where it has at least one borrower. We invert the scale of the HHI for ease of interpretation. A value of zero ($DIV = 0$) implies no diversification (all credit goes to borrowers from one country, what we will call *concentrated portfolio*), while higher values reflect increasing diversification of banks' loan portfolios across countries. We reason that banks with higher diversification have better access to funds during local financial shocks.

2.2 Data

For our main analysis and to construct banks' diversification, we use data on worldwide syndicated lending. We additionally use country-specific data and further information on borrowing firms' balance sheets. Loan-level data with detailed bank-firm relations comes from Thomson Reuters Dealscan and covers the universe of syndicated loans. Compustat (Global and US) provides firms' balance sheet information. Balance sheet data on banks come from Bankscope. Macroeconomic variables come from the World Bank's World Development Indicators. Finally, we use U.S. bank balance sheet data from FDIC's Statistics on Depository Institutions.

The Systemic Banking Crises Database presented by Laeven and Valencia (2013) provides country-year-level information on episodes of financial distress.[11] From 1995 to 2012, it reports 189 banking crisis (BC) observations. The two conditions that define a banking crisis are *i*) significant signs of financial distress in the banking system (such as bank runs, losses in the banking system, and/or bank liquidations); and *ii*) significant banking policy intervention measures in response to the losses in the banking system. In

[11] While there exist different databases on financial crises, Laeven and Valencia (2013) is the most comprehensive for banking crises occurring after 1970 (Bonner, van Lelyveld and Zymek, 2014).

our sample, there is a concentration of financial turmoil around the time of the Asian crisis and from 2008 onward, during the Great Financial Crisis.

To construct main variables, we use Dealscan data on syndicated loans. Syndicated lending constitutes a sizable share of total lending. Around one-third of total international lending is done through the syndicated loan market (Gadanecz and von Kleist, 2002) and it is an important source of financing in both developed and emerging economies (Cerutti, Hale and Minoiu, 2015). Thus, the syndicated loan market makes up for a significant share of total international lending and, hence, banks' total international loan portfolio. Syndicated loans are issued jointly by a group of banks to a single borrower. The lending syndicate includes at least one lead bank (also called lead arranger) and usually further participant banks. Lead banks negotiate terms and conditions of deals, perform due diligence, and organize participants. Therefore, lead arrangers stand in direct contact with the borrower and retain larger loan shares for signaling purposes (Saleem Ramadan, 2013). Participants are usually not in direct contact with the borrower, but merely supply credit. Compared to other types of bank loans, syndicated loans are on average larger in volume and issued to bigger borrowers.

Dealscan provides extensive information on syndicated loans at origination, including loan amount, maturity, and interest, as well as identity of lenders and borrowers. All data are aggregated at banks' and firms' parent level, consistent with the literature (Saleem Ramadan, 2013). The aggregation of banks at the parent level captures the ability of banks to make use of their internal capital market to allocate capital across borders.[12] We restrict our analysis to loans by banks to non-financial firms and consider lending only by commercial, savings, cooperative and investment banks.[13] We keep both lead arrangers and participants in our sample, and do so for two reasons. First, we are interested in banks' loan portfolio allocation across countries and not specific contractual frictions. As the focal point of our analysis is total credit supply, including both lead arrangers and participants provides a comprehensive picture of the syndicated loan market. Second, excluding participants leads to sample-selection bias. Lead arrangers are large banks operating on a global scale. We aim to compare banks along the dimension of their international diversification. Hence, excluding smaller participant banks with a rather concentrated portfolio will change the control group. Instead of comparing diversified

[12]Banks may choose to lend to a foreign firm either through direct cross-border lending or through a subsidiary in the foreign market.

[13]In Dealscan, we use lender types Commercial Banks, Finance Companies, Investment Banks, Mortgage Banks, Thrift/S&L, and Trust Companies. Investment banks constitute 3 % of our sample and excluding them does not change results. Borrower types included are Corporations, Insurance Companies, Law Firms, Leasing Companies and Other.

with concentrated banks, focusing on lead arrangers only will lead to a selected group of globally active banks in our sample. We would compare banks' diversification within a group of diversified and internationally integrated banks. To avoid this pitfall, we include leaders and participants in our analysis.[14]

TABLE 1: **Summary Statistics** ***(loan-level sample)***

Variable	Obs	Mean	Std. Dev.	Min	Max	P50
Δ loan volume	1724073	.02	.35	-1.25	1.44	0
loan volume (m)	1724073	78.9	147.8	.01	974.96	28.33
loan spread (bp)	1365464	162.54	114.44	15	533.19	138.5
maturity (months)	1723449	73	41.75	12	252	60

Note: This table shows descriptive statistics on the bank-firm-year (loan) level. *loan volume* (in m USD) is the outstanding loan volume of bank b to firm f at year t. Δ *loan volume* is the log difference of *loan volume* by year t. Loan spread is the All-in-Draw Spread (in bps) coming from Dealscan. Maturity is the maturity of the loan at origination (in months). All data is winsorized at the 1^{st} and 99^{th} percentile of its distribution at the bank-firm-year level; thus, maximum values may differ from Table 2. For detailed variable definitions see Table 23 and text.

TABLE 2: **Summary Statistics** ***(firm-level sample)***

Variable	Obs	Mean	Std. Dev.	Min	Max	P50
Δ loan volume	196446	.04	.39	-7.87	9.94	0
loan volume (m)	192617	446.09	860.44	.05	8310.12	126
loan spread (bp)	141777	201.34	121.28	15	855	188.64
maturity (months)	196815	71.72	46.6	12	370	60
Δ employment	52295	.03	.19	-.98	.99	.02
Δ investment	55377	.03	.62	-2.94	2.43	.06
Δ sales	57674	.08	.27	-7.49	9.22	.07
investment ratio	56714	.22	.97	-.27	175.87	.17
return on assets	59421	.06	.1	-.93	.34	.07
employment (th)	55216	11.1	27.71	0	583.83	2.66
log total assets	61508	7.44	2.4	1.81	15.27	7.19
market to book ratio	40532	1.6	1.08	.19	60.86	1.3
long-term debt ratio	62092	.25	.21	-.01	4.48	.21

Note: This table shows descriptive statistics on the firm-year (firm) level. The first four rows contain data on the full sample coming from Dealscan. From row five onward, the sample shrinks after the match with firms in Compustat. All data is winsorized at the 1^{st} and 99^{th} percentile of its distribution at the firm-year level; thus, maximum values may differ from Table 1. For detailed variable definitions see Table 23 and text.

[14] For more information on the syndicated loan market's institutional setting see Berg, Saunders and Steffen (2016).

Loan level We decompose syndicated loan deals into loan portions provided by each lender to obtain granular credit level data. Whenever Dealscan provides information on lending shares of each bank, we use this information to split loan volume accordingly (available for 28 % of the deals).[15] In cases where lending shares are missing we split loan volume on a pro-rata basis among all banks in a syndicate.[16] Transactions with deal status 'canceled', 'suspended', or 'rumor' are removed and all loan nominations transformed into million U.S. Dollars (USD) using the spot exchange rate at origination, provided by Dealscan. If after this allocation procedure the loan portion is smaller than 10,000 USD, we drop the observation to remove erroneously small loans (0.6 % of observations). Overall, we split a total of 293,163 deals into 1,638,343 loan portions. We next use the loan portions to construct each bank's outstanding loan volume as a stock variable to proxy the loan's entry on the loan book (Morais, Peydro and Ruiz Ortega, 2019). Each outstanding loan remains active until the end of its maturity. We aggregate all outstanding loan portions between a bank-firm combination to obtain bank b's outstanding loan volume to firm f in year t, which we define as a loan observation. Summary Statistics at the loan level are shown in Table 1.

To measure banks' geographic diversification, we construct their distribution of cross-border loans by destination country. Therefore, geographic diversification is based on the nationality of the borrower at origination and not defined by the nationality of the parent bank.[17] For each year, we then aggregate all outstanding loans by each bank to all borrowers from country j and divide by its total outstanding loans to obtain country shares $s_{b,j,t}$. We calculate *diversification* according to Equation (1).

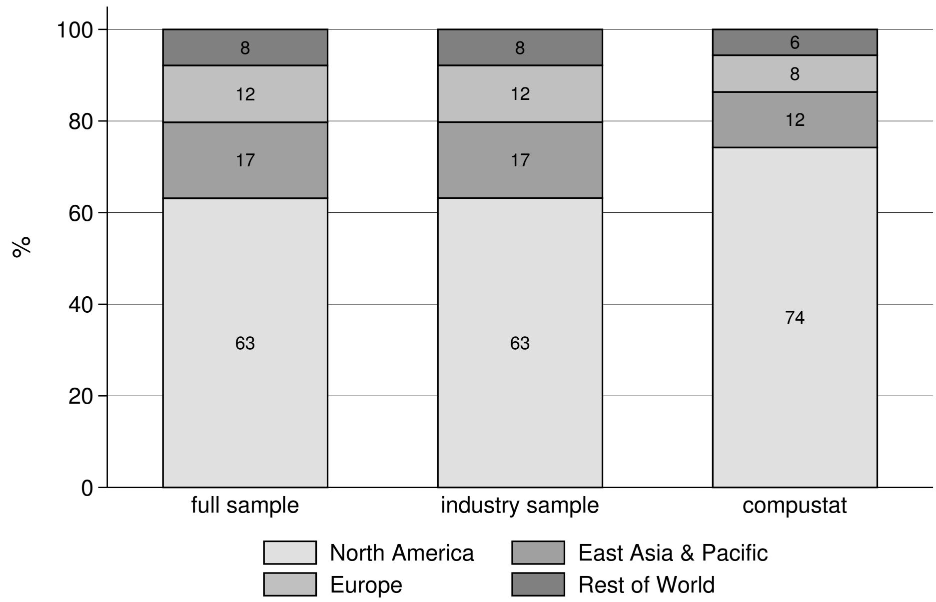
We merge lending banks active in Dealscan with balance sheet data from Bankscope. To link Dealscan with Bankscope, we match the ultimate parent of the parent institution in Dealscan with the bank holding company in Bankscope by hand using name, address, newspaper reports and bank websites as information. We are able to successfully merge 229 institutions. As the matched banks tend to be the largest banks in a highly concentrated market, this covers 631,143 observations or 37 % of the loan-level sample. Thus, we obtain balance sheet data on banks' total assets, share of wholesale deposits, tier 1 capital ratio, leverage ratio, and return on equity.

[15] See Giannetti and Laeven (2012); De Haas and Van Horen (2013)

[16] In the sub-case of partial information on loan shares, we first use the available information to allocate loan shares. Then, we split the remaining amount equally among banks with missing information. If the sum of the allocation rule is larger than 110 % we consider this an erroneous entry and treat it as if lending share information was not available in the first place.

[17] In robustness checks, we use an alternative measure based on parent bank nationality.

Figure 1: **Firm level Sample Change**



Note: This figure shows the change in sample composition for our different specifications on the firm level. Left bar: full sample with no fixed effects. Middle bar: sample once we use industry*time fixed effects. Right bar: sample limited to firms with balance sheet information.

Table 3: **Geographic Distribution by Region** ***(loan level sample)***

	loans	firms	banks	DIV	BC
East Asia and Pacific	386973	8767	1642	266	28
Europe and Central Asia	379177	6033	1118	269	128
Latin America and Caribbean	39622	626	126	21	24
Middle East and North Africa	30164	334	176	54	0
North America	860634	19176	3711	74	6
South Asia	20379	458	116	8	0
Sub-Saharan Africa	7124	116	73	14	3
Total	1724073	35510	6962	706	189

Note: This table shows the geographic distribution of our sample. *loans* denotes the number of firm-bank-year observations, *firms* and *banks* the number of individual firms and banks. *DIV* stands for diversification and denotes the number of banks with non-zero portfolio diversification. Finally, *BC* stands for banking crisis and denotes the number of country-year observations with banking crises. For detailed variable definitions see Table 23 and text.

Firm level To examine effects of credit supply on firm behavior, we merge our data set with firm balance sheet information. We aggregate the firm-bank-year data to the firm-year level and then match borrowers in Dealscan with firms in Compustat (Global & US). For merging we use the file provided by Chava and Roberts (2008). Combining Dealscan with Compustat reduces observations, since information for some firms, especially smaller ones, are missing in Compustat. Overall, we are able to successfully match around 32 % of our firm-year observations. This linking exercise gives rise to a selection bias into larger firms that are less financially constrained. Figure 1 shows that the geographic composition changes only slightly after matching firms with Compustat, while Table 3 gives a detailed geographic breakdown. Thus, we expect this selection bias to render the estimates of the real effects to become more conservative. The reason being that the effect of a negative loan supply shock on firm performance is found to be larger for smaller firms with less financial leeway in previous studies (Cohen and Pascaline, 1997). We use information on firms' syndicated loan volume, investment, employment, total assets, sales and fixed assets, where we compute growth rates as log differences. Summary statistics at the firm-level are shown in Table 2.

Figure 2: **Histogram of Banks' Geographic Diversification *(loan-level sample)***

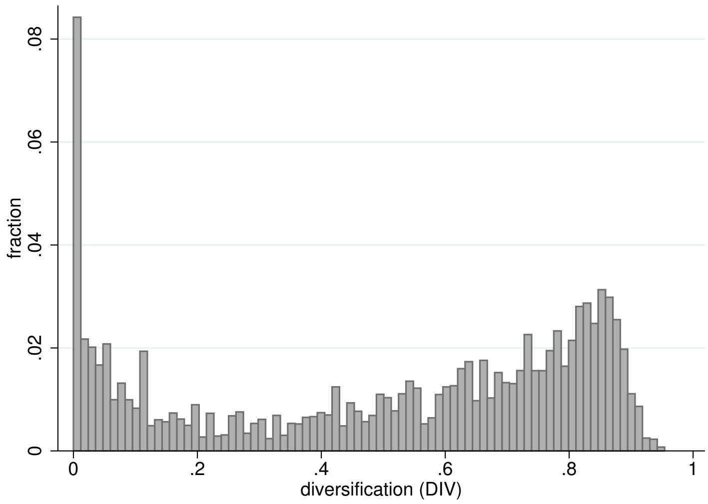
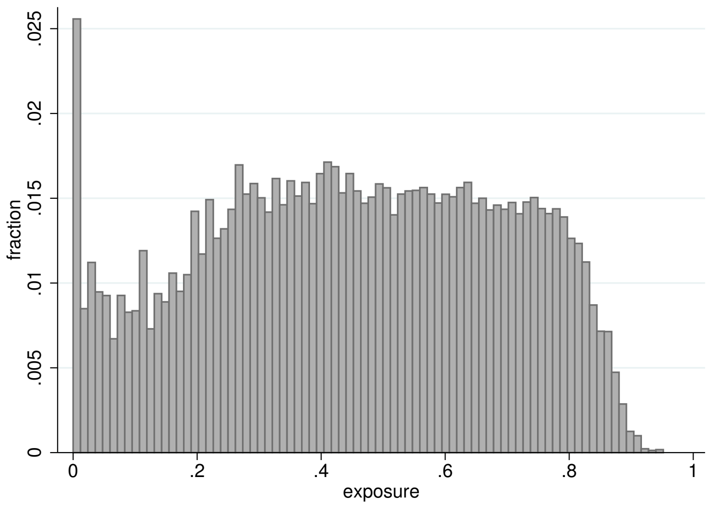


Figure 3: **Histogram of Firms' Exposure to Diversified Banks *(firm-level sample)***



Note: Figure 2 shows the loan-level distribution of banks' diversification, Figure 3 the firm-level distribution of firms' exposure. The mass of observations shifts from the right tail towards the middle, indicating that most firms borrow from both diversified and concentrated banks in each year. For detailed variable definitions see Table 23 and text.

2.3 Descriptive Statistics

Figures 2 and 3 show the distribution of *diversification* on the loan level and *exposure* on the firm level. About 8 % of all loans are extended by banks with no geographic diversification. The remaining banks have at least some diversification, with a bunching around 0.9. Figure 3 shows that more than 97 % of firms borrow from at least one bank with non-zero geographic diversification. The median (mean) firm has 4 (8) bank connections in a given year. This suggests that firms accessing the syndicated loan market are potentially able to substitute across lenders during crises. The median (mean) number of outstanding loans by banks per year is 2 (33).

Our sample covers the years 1995 to 2012 and includes information on 35,510 firms and 6,962 banks forming a total of 1,724,073 firm-bank-year observations, and 194,726 firm-year observations (9,393 firms and 60,953 observations for the matched Compustat sample). There are a total of 2,046 banks with some diversification and 4,916 banks with zero geographic diversification. The median (mean) value of *diversification* for banks with non-zero diversification is 0.41 (0.40). The group of diversified banks extends around 93 % of all loans, which reflects that they are large lenders. Table 3 highlights the geographical distribution of loans, firms, and banks by region. The majority of loans are extended to borrowers located in Europe, East Asia and Pacific, and North America. Moreover, countries in Europe and Asia have the highest number of geographically diversified banks.[18] North American banks are less diversified as they lend mostly to borrowers located in the U.S. or Canada. Finally, the highest incidence of banking crises occurs in Europe, Asia, and, to a lesser extent, in Latin America.

[18] We split geographic diversification along the annual median and denote banks with an above median value as diversified.

Table 4: **Summary Statistics – Diversified vs. Concentrated Banks *(full sample)***

	diversified		**concentrated**		**mean diff.**
	mean	sd	mean	sd	t
Δ loan volume	0.02	(0.36)	0.01	(0.34)	-17.00
loan volume (m)	101.67	(296.04)	75.53	(266.63)	-60.94
loan spread (bp)	137.08	(107.52)	191.17	(131.07)	263.55
maturity (months)	76.12	(49.16)	71.39	(42.22)	-67.76
Observations	854370		869703		1724073

Note: This table shows descriptive statistics on the firm-bank-year (loan) level. The sample is split by the yearly median according to banks' diversification. Highly diversified observations are denoted *diversified*, those with low diversification as *concentrated*. *mean* denotes the mean, *sd* the standard deviation, and *mean diff.* the t-value for the difference in means across both groups. For detailed variable definitions see Table 23 and text.

Table 5: **Summary Statistics – Diversified vs. Concentrated Banks *(Bankscope sample)***

	diversified		**concentrated**		**mean diff.**
	mean	sd	mean	sd	t
diversification (DIV)	0.74	(0.18)	0.20	(0.22)	-64.94
log(assets)	12.14	(1.96)	11.09	(1.88)	-12.24
tier 1 capital ratio	10.26	(5.27)	10.50	(3.55)	-0.34
share wholesale deposits	0.29	(0.23)	0.26	(0.29)	-3.13
leverage ratio	0.05	(0.03)	0.07	(0.03)	10.06
return on equity	7.60	(18.83)	8.92	(18.52)	1.41
Observations	863		873		1736

Note: This table shows descriptive statistics on the bank-year (loan) level for the Dealscan-Bankscope matched sample. The sample is split by the yearly median according to banks' diversification. Highly diversified banks are denoted *diversified*, those with low diversification as *concentrated*. *mean* denotes the mean, *sd* the standard deviation, and *mean diff.* the t-value for the difference in means across both groups. For detailed variable definitions see Table 23 and text.

Tables 4−7 provide summary statistics of main variables. We split the respective samples by diversification or exposure.[19] For the syndicated loan market, Table 4 shows that loans by geographically diversified banks are larger, have lower interest rates, and are issued at longer maturity than loans by banks with geographically more concentrated portfolios. The large difference in loan volume suggests that geographically diversified banks are on average larger than their less diversified counterparts.

Table 5 shows that diversified banks are significantly larger, have a higher share of wholesale deposits, and a lower leverage ratio (for the sample of banks we succesfully match to Bankscope). The difference in bank balance sheets highlights the need to control for observable and unobservable bank characteristics. In Table 6 the average firm with an above median exposure to diversified banks obtains loans with larger volume, lower interest rates and longer maturity compared to firms with fewer relationships with diversified banks. Table 7 restricts the sample to firms with balance sheet information. Borrowers with high exposure to diversified banks tend to grow slower and are larger than their peers borrowing from banks with a geographically concentrated portfolio. Long-term debt as share of total assets is similar across both groups indicating that they are on average comparable in terms of their need for external finance. Overall, the difference in firm characteristics highlights the need to control for loan demand.

[19] Again, we split geographic diversification along the annual median and denote banks with an above median value as diversified. Same goes for exposure.

Table 6: **Summary Statistics – High Exposure vs. Low Exposure Firms *(full sample)***

	high exposure		**low exposure**		**mean diff.**
	mean	sd	mean	sd	t
Δ loan volume	0.04	(0.39)	0.03	(0.39)	-2.34
loan volume (m)	763.80	(1982.62)	323.47	(723.77)	-65.52
loan spread (bp)	169.81	(130.74)	235.06	(137.16)	92.05
maturity (months)	83.62	(64.15)	64.91	(42.38)	-76.95
Observations	99948		99986		199934

Note: This table shows descriptive statistics on the firm-year (firm) level for the full sample of Dealscan firms. The sample is split by the yearly median according to firms' exposure. High exposure firms are denoted *high exposure*, those with low exposure as *low exposure*. *mean* denotes the mean, *sd* the standard deviation, and *mean diff.* the t-value for the difference in means across both groups. For detailed variable definitions see Table 23 and text.

Table 7: **Summary Statistics – High Exposure vs. Low Exposure Firms *(Compustat sample)***

	high exposure		**low exposure**		**mean diff.**
	mean	sd	mean	sd	t
Δ employment	0.03	(0.17)	0.03	(0.20)	2.96
Δ investment	0.03	(0.59)	0.04	(0.64)	2.66
Δ sales	0.07	(0.32)	0.09	(0.22)	6.66
investment ratio	0.22	(1.39)	0.23	(0.26)	1.71
return on assets	0.06	(0.08)	0.06	(0.11)	-4.76
employment (th)	17.04	(37.40)	6.48	(15.09)	-45.22
log total assets	8.51	(2.30)	6.48	(2.06)	-115.61
market to book ratio	1.58	(1.01)	1.61	(1.11)	2.06
long-term debt ratio	0.25	(0.20)	0.24	(0.22)	-7.53
Observations	29613		33168		62781

Note: This table shows descriptive statistics on the firm-year (firm) level for the smaller sample of matched Compustat firms. The sample is split by the yearly median according to firms' exposure. High exposure firms are denoted *high exposure*, those with low exposure as *low exposure*. *mean* denotes the mean, *sd* the standard deviation, and *mean diff.* the t-value for the difference in means across both groups. For detailed variable definitions see Table 23 and text.

2.4 Empirical Strategy and Identification

To analyze lending behavior by geographically diversified banks and their effect on firms, we use two aggregation levels. To isolate loan supply from loan demand, we begin on the firm-bank-year level (*loan level*). Then, we aggregate the data to the firm-year level (*firm level*) to examine substitution across loans, as well as real effects on firms.

Loan level: Our baseline specification tests how geographic diversification (DIV) affects loan volume for each firm-bank pair. To see whether diversification has a positive effect on loan supply during financial turmoil in the borrower country, we interact diversification with a banking crisis dummy (BC):

$$log(loan)_{f,b,t} = \beta_1 \ BC_{c,t} + \beta_2 \ DIV_{b,t-1} + \beta_3 \ BC_{c,t} \times DIV_{b,t-1} + \phi_{f,b} + \tau_t + \varepsilon_{f,b,t}. \quad (2)$$

The dependent variable $log(loan)$ denotes the log of outstanding loan volume of firm f from bank b in year t. Banking crisis dummy $BC_{c,t}$ is at the country level and takes value one during a crisis in firm country c in year t. $DIV_{b,t-1}$ is the geographic diversification index on the bank-year level. We lag DIV by one period to avoid contemporaneous effects of the banking crisis on banks' diversification.[20] $\phi_{f,b}$ are firm*bank fixed effects, and τ_t are either firm*year or country*industry*year fixed effects. We cluster standard errors on the firm-country*year level to account for correlation within the same borrower country across firms. Regression (2) is similar in spirit to a difference-in-difference regression. The coefficient of interest β_3 reflects the change in loan supply by diversified banks minus the change in loan supply by concentrated banks. If diversified banks have better access to funds during crises, their loan supply is higher compared to less diversified banks. This is, we expect $\beta_3 > 0$.

The key identification challenge is to absorb changes in loan demand to isolate loan supply. Firms borrowing from diversified banks are on average bigger, so loan demand is likely to be correlated with banks' geographic diversification. Due to the granularity of our data, we can overcome this issue. First, firm*bank fixed effects exploit the variation within the same firm-bank combination over time and control for unobservable and time-invariant bank and firm heterogeneity (such as industry, location or average size), as well as for unobservable time-invariant characteristics at the bank-firm level, such as relationship or distance. Second, firm*time fixed effects allow shocks to affect each firm at each point in time heterogeneously. Thereby we control for unobservable time-varying

[20]We assume that a firm's bank relationship can be proxied by its previous year credit dependence. This builds on the finding of Smith, Ongena and Smith (2016) and Cohen and Pascaline (1997) that banking relationships are sticky over time.

firm fundamentals (such as profitability, risk, and other balance sheet characteristics) to identify credit supply.[21] Essentially we are comparing the same firm borrowing from different banks in a given year, while using only the within variation of each bank-firm combination for estimation (Jiménez, Atif, Peydro and Saurina Salas, 2012). After absorbing any changes in loan demand our estimates reflect loan supply effects.[22]

Since diversification (DIV) is a choice variable, it raises concerns about endogeneity in Equation (2). We do not have a bank level instrument to directly solve the problem. Instead, we make indirect attempts to address the issue. First, we include bank*year fixed effects to control for unobservable time-varying bank characteristics, for example bank size, risk taking, or capital ratios. With bank*year fixed effects, we hold all time-varying unobservable bank characteristics constant and compare lending by the *same* bank to the *same* firm (due to firm*time fixed effects) at different levels of diversification. Second, we directly control for observable determinants of diversification at the bank-year level ($X_{b,t}$), interacted with *banking crisis* ($BC_{c,t}$). If the controls explain both banks' level of diversification and their lending during crises, then controlling for their interaction allows us to isolate the direct effect of diversification on lending. For example, diversified banks could be larger. If larger banks maintain relatively higher loan supply during local crises, the coefficient on diversification would be biased. We match a sub-sample of banks in Dealscan with bank balance sheet data in Bankscope. Bank characteristics we deem important predictors of diversification are bank size (log assets), Tier 1 capital ratio, the share of wholesale deposits over total deposits, leverage ratio, and return on equity. To test how important these balance sheet items are in explaining bank diversification, we estimate regressions with diversification as dependent variable and bank covariates as explanatory variables.

Table 8 shows that bank size and share of wholesale deposits are statistically and economically significant explanatory variables of diversification. We use two dependent variables, diversification as continuous variable (defined in Equation (1)) and as a dummy with value one for banks with diversification above the yearly median. Columns (1) and

[21]For each firm-year pair, firm*time fixed effects require observations from at least two banks. On the syndicated loan market, around 97 % of all loans satisfy this condition. The sample selection effect due to this demanding specification is therefore negligible.

[22]Note that with granted loans, firm*year fixed effects may not fully address demand (Paravisini, Rappoport and Schnabl, 2015), since they control for general changes in firm level characteristics, but not differential demand by firms across banks. With this caveat in mind, generally the Khwaja-Mian approach is a reasonable approximation to firms' loan demand. To mitigate the problem of bank-firm selection, we repeat our analysis on the restricted sample of firms that borrow from both diversified and concentrated banks in each year (Khwaja and Mian, 2008). Coefficients for the reduced sample have the similar sign, size and significance as for the full sample (unreported).

Table 8: **Determinants of bank diversification**

VARIABLES	(1) DIV (cont)	(2) DIV (median)	(3) DIV (cont)	(4) DIV (median)
log(assets)	0.044***	0.051***	0.071***	0.005
	(0.011)	(0.019)	(0.023)	(0.042)
tier 1 capital ratio	0.001	-0.003	-0.001	-0.001
	(0.003)	(0.006)	(0.001)	(0.002)
share wholesale deposits	0.364***	0.407***	-0.058	-0.255*
	(0.091)	(0.139)	(0.049)	(0.141)
leverage ratio	-0.015	-0.025	0.010*	-0.015
	(0.010)	(0.016)	(0.005)	(0.012)
return on equity	0.001**	0.001	0.000	-0.000
	(0.001)	(0.001)	(0.000)	(0.001)
Observations	1,045	1,045	1,038	1,038
R-squared	0.206	0.117	0.934	0.803
Bank FE	-	-	Yes	Yes
Cluster	Bank	Bank	Bank	Bank

Note: This table shows determinants of bank diversification, as defined in equation (1) at the bank-year level for the Dealscan-Bankscope matched bank sample. Dependent variable is *diversification* or a dummy with value one if diversification is above the yearly median, and zero if below. Bank balance sheet data are from Bankscope. For detailed variable definitions see Table 23 and text. All standard errors are clustered at the bank level. *** p<0.01, ** p<0.05, * p<0.1

(2) compare levels of diversification across banks. *log(assets)* and *share wholesale deposits* have positive coefficients, significant at the 1 % level, indicating that diversified banks differ in terms of size and funding structure from concentrated banks. Since our baseline regression (Equation (2)) includes bank*firm fixed effects, they are exploiting *within*-bank variation. Hence, columns (3) and (4) replicate columns (1)-(2), but add bank fixed effects. Only size remains a significant predictor for diversification. As we will show below, both methods − including bank*year fixed effects and bank characteristics interacted with the crisis dummy − leave main estimates similar in terms of sign and significance, with only modest changes in magnitude. These findings alleviate concerns about omitted variable bias, despite the lack of a proper instrument for diversification.

Firm level: On the loan level we observe whether credit at the firm-bank level changes differentially during crises, depending on the type of lender. However, the analysis neglects potential substitution effects and remains silent about the real effects of loan supply on firms. If firms can easily substitute syndicated loans from banks that reduce loan supply with loans by banks that increase loan supply, the substitution offsets the credit contraction of individual banks. In this case, firm exposure to geographically diversified banks becomes irrelevant for firms' syndicated loan growth. Beyond the syndicated loan market, firms may also be able to substitute a fall in syndicated lending through other debt instruments, for example non-syndicated credit or corporate bonds. Such a substitution would imply that we do not find any effect of bank diversification on firms' total debt or investment, *even if* we find an effect on firms' syndicated loan growth. Loan supply only has real effects on firm performance if firms can at most partially substitute the fall in credit.

To test for substitution and real effects, we run the following firm-level regression:

$$\Delta y_{f,t} = \gamma_1 \ BC_{c,t} + \gamma_2 \ exposure_{f,t-1} + \gamma_3 \ BC_{c,t} \times exposure_{f,t-1} + \phi_f + \tau_{c,i,t} + u_{f,t}, \quad (3)$$

In the baseline specification, the dependent variable $\Delta y_{f,t}$ is the log difference of outstanding syndicated loan volume of firm f to *all* its lenders in year t. In further regressions, we use the log difference of total long-term debt to test for substitution into non-syndicated debt instruments. To analyze real effects, we also use investment and employment growth in log differences. Banking crisis dummy ($BC_{c,t}$) varies at the country-level and equals one during banking crisis years in the firm country c. $exposure_{f,t-1}$ is the share of firms f's outstanding credit from diversified banks, lagged by one period. ϕ_f denote firm fixed effects, and $\tau_{c,i,t}$ denote time-varying country*industry*year fixed effects, where c and i denote firm f's country and industry. For our Compustat sample we additionally control for time-varying firm demand by including return on assets, leverage, and log of assets. We cluster standard errors at the firm level in all estimations.

Our main coefficient of interest, γ_3, is on the interaction term ($BC \times exposure$). γ_3 is the firm level counterpart of β_3, which is the estimated interaction coefficient ($BC \times DIV$) from loan level Equation (2). It shows the change in loan growth for high exposure firms minus the change in loan growth for low exposure firms. If firms can perfectly substitute a fall in lending by one bank with other forms of financing, then $\gamma_3 = 0$ in the respective regression. In turn, a non-zero estimate of γ_3 suggests imperfect substitution. We expect $\gamma_3 > 0$, as higher exposure to diversified banks should lead to higher loan growth during crises.

To identify loan supply, we employ country*industry*time fixed effects to absorb time-varying demand changes for each industry in each country. The identifying assumption is that all firms within one industry of one country change their loan demand equally. How reasonable is it to assume no heterogeneity in firm demand within industries? If there is differential loan demand within industries, our coefficient is biased and does not reflect supply effects. We test the validity of this identifying assumption on the loan-level, where we compare estimates using country*industry*time fixed effects with estimates employing the more rigorous firm*time fixed effects.[23] As we will show, coefficient are close, but somewhat larger under country*industry*time fixed effects, so we interpret our firm-level estimates as upper bounds of the true effect.

3 Results

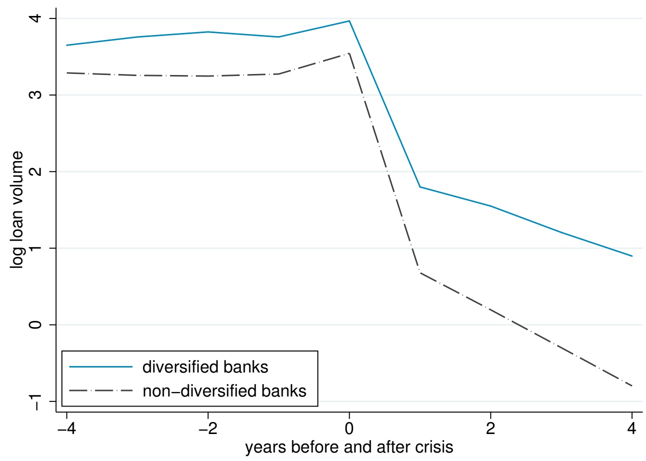
In Section 3.1 we first establish on the loan level that diversified banks smooth local financial shocks, relative to non-diversified banks. Time-varying borrower-fixed effects control for changes in firm demand to isolate supply effects. To examine real effects, we then aggregate to the firm level and show that firms with higher exposure to diversified banks have stronger loan, investment, and employment growth during banking crises. Section 3.2 sheds light on the underlying mechanism and shows that geographic diversification improves banks' access to funding.

Before moving to the regression analysis, Figure 4 shows the stabilizing effect of diversified banks in a non-parametric way. Panel 4a plots log loan volume in the four years prior, during, and after a banking crisis. We split loans into loans by diversified (blue solid line) and non-diversified (dashed black line) banks according to the yearly median of *diversification*. Loan volume follows a similar trend for diversified and non-diversified banks in the years preceding a crisis. However, it diverges sharply during the crisis. Both types of banks see a sharp and persistent contraction in loan volume, but the decline is almost twice as strong for non-diversified banks. The divergence in loan volume is because of banks' portfolio diversification and we will estimate it as the difference in the change in loan supply by diversified banks and the change in loan supply by concentrated banks (coefficient β_3 in regression (2)). We now confirm that the pattern shown in Figure 4 holds in regression analysis.

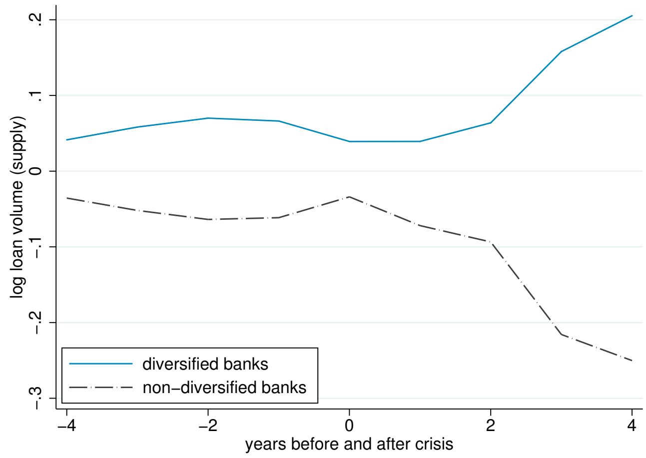
[23] Our baseline sample requires each country-industry-year pair to have at least two firms. When we use firm*time fixed effects, we lose around 2 % of observations, as some firms only have one lender connection.

Figure 4: **Loan Volume during Crises**

(a) Total loan volume



(b) Loan supply



Note: Both panels show the evolution of log(loan volume) in the four years prior, during, and the four years after a banking crisis. A value of 0 on the x-axis denotes the year of the banking crisis. We split the sample by the yearly median for banks with high and low values of diversification. Panel 4a shows the unconditional average across all banks. Both diversified and concentrated banks see a decline in outstanding loan volume during the crisis and the following years, but concentrated banks see a stronger fall. Panel 4b plots the residual of a regression of log(loan volume) on firm*time fixed effects that absorb unobservable change in loan demand. After absorbing demand effects, both lines reflect changes in loan supply. Diversified banks do not reduce loan supply during the crisis and increase it in the following years, while concentrated banks reduce loan volume during and after the crisis. For detailed variable definitions see Table 23 and text.

3.1 Main Results

Loan level: Table 9 reports results for regression Equation (2) and shows that diversified banks maintain higher loan growth during banking crises, relative to non-diversified banks. The dependent variable is log loan volume. Column (1) looks at variation within each firm-bank connection by using fixed effects on the firm*bank level. Diversified banks extend loans with higher volume in general, as indicated by the positive coefficient on *diversification*. The coefficient of interest (β_3) on the interaction term ($DIV \times BC$) is highly significant and positive. During banking crises, increasing diversification by one standard deviation increases loan volume by ($0.31 \times 0.135 =$) 4.2 %. To ensure that the positive effect is due to supply effects, column (2) adds firm*time fixed effects to absorb any time-varying changes in firm demand.[24] Borrowing from a diversified bank is now not statistically different to borrowing from a non-diversified bank during non-crisis times. The positive effect of diversified banks during banking crises remains significant: increasing diversification by one standard deviation during a banking crisis increases firms' loan volume by 1.2 %. Borrowing from a fully diversified bank ($DIV = 1$) increases the positive effect to 3.9 %, compared to borrowing from banks with an entirely concentrated portfolio ($DIV = 0$). Comparing columns (1) and (2), we see that absorbing demand effects reduces the coefficient on the interaction term by around two-thirds. The change in size suggests that diversified banks lend to borrowers of higher resilience and better quality during crises.[25] However, after controlling for loan demand, there remains a positive and significant loan supply effect associated with higher geographic diversification.

Figure 4, Panel 4b plots log loan volume after removing loan demand effects through firm*time fixed effects.[26] Comparing it to Panel 4a, we see that demand effects explain a large part of the overall decline in loan volume. Strikingly, after removing demand effects, diversified banks maintain their loan supply during the crisis and increase it in the following years. Non-diversified banks reduce loan volume persistently. The increase in loans by diversified banks suggests that there is substitution in lending across banks − a notion we will confirm in Section 5. As in Panel 4a, loan supply follows a similar trend for both bank types prior to the crisis. By absorbing any changes in firms' loan demand,

[24]The coefficient on banking crisis is now absorbed by firm*year fixed effects.

[25]In Section 3.2 we show that firms with higher exposure to diversified banks are less risky and have lower volatility in terms of sales and asset growth.

[26]We plot the residual of a regression of log(loan volume) on firm*time fixed effects that absorb any unobservable change in firms' loan demand. After absorbing demand effects the residual reflects banks' credit supply.

TABLE 9: **Loan Supply during Banking Crises *(loan-level)***

VARIABLES	(1) log(loan vol)	(2) log(loan vol)	(3) log(loan vol)	(4) log(loan vol)	(5) log(loan vol)	(6) log(loan vol)
banking crisis (BC)	0.040					
	(0.029)					
diversification (DIV)	0.309***	0.005	0.013			
	(0.060)	(0.018)	(0.017)			
DIV × BC	0.135***	0.039***	0.063***	0.072**	0.127***	0.103**
	(0.026)	(0.013)	(0.013)	(0.037)	(0.049)	(0.048)
log(assets) × BC						0.016**
						(0.006)
WS deposits × BC						0.057*
						(0.033)
Tier 1 capital ratio × BC						0.000
						(0.000)
leverage ratio × BC						0.006*
						(0.003)
return on equity × BC						-0.000
						(0.000)
Observations	1,724,073	1,691,064	1,724,073	1,621,124	474,784	474,784
R-squared	0.954	0.976	0.965	0.978	0.978	0.978
Firm*Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm*Year FE	-	Yes	-	Yes	Yes	Yes
Country*Industry*Year FE	-	-	Yes	-	-	-
Bank*Year FE	-	-	-	Yes	Yes	Yes
Cluster	Country*Year	Country*Year	Country*Year	Country*Year	Country*Year	Country*Year

Note: This table shows regressions on the bank-firm-year (loan) level. The dependent variable is log of total outstanding loan volume; *banking crisis (BC)* is a dummy with value one during banking crises in the firm country, as defined in Laeven and Valencia (2013); *diversification (DIV)* is banks' portfolio diversification. Columns (1)-(4) are on the full sample; Columns (5)-(6) are on the matched Dealscan-Bankscope sample. For detailed variable definitions see Table 23 and text. All standard errors are clustered at the firm country-year level. *full sample* denotes the full sample with all loan-level observations, while *KM sample* restricts the sample to firms that borrow from diversified and concentrated banks in each year. *** p<0.01, ** p<0.05, * p<0.1

Panel 4b provides a clean identification of the stabilizing effect of portfolio diversification on loan supply.

When we move to the firm level, we can no longer control for credit demand through firm*time fixed effects. Instead, we use country*industry*year fixed effects, so we assume that firms within the same country-industry-year pair change demand similarly. To verify this assumption, column (3) runs the loan level regression with country*industry*year fixed effects. Comparing coefficients with column (2) indicates how appropriate we capture demand effects. The coefficient of interest has the same sign and significance, but is larger in column (3). Controlling for time-varying industry demand leads to an overestimation of the effect by about one third. The increase in the coefficient on $DIV \times BC$ suggests that even within four-digit industries, there is variation in loan demand.[27] We therefore interpret our firm level results as an upper bound of the true effect.

[27] Note that the standard deviation of *diversification* is 0.089 for each firm-year pair, but 0.072 for each country-industry-year pair. Adjusting for the difference in variation reduces the difference between both columns to about 20 %.

Firm*time fixed effects control for loan demand. However, it could still be that diversified banks fundamentally differ from concentrated banks. For instance, Table 4 shows that diversified banks are larger in terms of total assets. To account for observable and unobservable differences across banks that could be related to diversification, columns (4)-(6) include bank*time fixed effects and bank balance sheet items. Including bank*time fixed effects in addition to bank*firm and firm*time fixed effects controls for unobservable time-varying bank characteristics, for example bank size, risk taking, capital, or bank nationality. Column (4) thus compares lending by the *same* bank to the *same* firm during a crisis at different levels of diversification − this is, we hold all unobservable bank characteristics constant. Compared to column (2), the coefficient of interest almost doubles in magnitude (the coefficient on diversification is now absorbed by fixed effects), suggesting that the positive effect of diversification is not explained by unobservable bank characteristics.

While the positive and significant coefficient on $DIV \times BC$ suggests that bank diversification has a positive effect on loan supply conditional on basic bank covariates, it could still be that bank controls have a *marginal* effect during crises. We thus include bank balance sheet items, interacted with the banking crisis dummy, in column (6). Since the matched Dealscan-Bankscope sample leads to a drastic fall in the number of observations, column (5) first shows that within the sample of banks for which we obtain balance sheet information, diversification has a positive effect on loan supply (after controlling for bank*firm, firm*time, and bank*time fixed effects). Relative to the baseline specification in column (4), the coefficient of interest increases in size. However, the standard deviation of DIV on the reduced sample is now 0.24, compared to 0.31 for the full sample, yielding comparable magnitudes in terms of economic significance. Once we include the interaction terms in column (6), the coefficient on $DIV \times BC$ remains positive and significant, and close in magnitude to column (5). While large banks and banks with a higher share of wholesale deposits also exhibit higher loan supply during local crises, diversification still matters. All in all results in Table 9 show that diversified banks sustain higher loan supply during crisis times, relative to banks with a concentrated loan portfolio; and that the effect is robust to bank size, bank funding structure, as well as unobservable bank characteristics.

Firm level: Loan-level regressions identify changes in individual firm-bank connections. If firms can substitute between bank types during banking crises, changes in individual loans need not affect firms. Suppose a firm borrowing from a non-diversified bank sees a contraction in loan supply. Forming a new borrowing relationship with a

Table 10: **Loan Growth by Firm Exposure to Diversified Banks *(firm-level)***

VARIABLES	(1) Δ loan volume	(2) Δ loan volume	(3) Δ loan volume
banking crisis	-0.142***		
	(0.006)		
exposure	-0.475***	-0.185***	-0.182***
	(0.019)	(0.021)	(0.022)
exposure × BC	0.055***	0.050***	0.039**
	(0.014)	(0.017)	(0.019)
Observations	196,337	196,337	196,038
R-squared	0.138	0.172	0.317
Firm FE	Yes	Yes	Yes
Country*Year FE	-	Yes	-
Country*Industry*Year FE	-	-	Yes
Cluster	Firm	Firm	Firm

Note: This table shows regressions on the firm-year (firm) level. The dependent variable is log difference of firms' total outstanding loan volume; *banking crisis (BC)* is a dummy with value one during banking crises in the firm country, as defined in Laeven and Valencia (2013); *exposure* is firms' exposure to diversified banks. For detailed variable definitions see Table 23 and text. All standard errors are clustered at the firm level. *** p<0.01, ** p<0.05, * p<0.1

diversified bank mitigates the negative credit supply shock. To examine whether credit supply shocks have real effects, we aggregate to the firm-year level. Tables 10 and 11 show results for estimating regression Equation (3). Firms with higher exposure to diversified banks fare better during banking crises, relative to firms with low exposure.

In Table 10, column (1) controls for unobservable time-invariant firm characteristics through firm fixed effects. The dependent variable is loan growth $\Delta loan_{f,b,t}$. In line with expectations, the coefficient on *exposure* is negative, because diversified banks lend predominately to larger firms in developed economies, which have lower average growth rates. The negative coefficient on banking crisis implies that borrowers' credit growth declines by 14.2 % during banking crises when they have no connections to diversified banks (exposure= 0). Higher exposure to diversified banks attenuates the negative effect. The coefficient on the interaction term of exposure and banking crisis ($exposure \times BC$) is positive and statistically significant at the 1 % level. Increasing exposure from the 25^{th} to 75^{th} percentile increases loan growth during a crisis by $(0.39 \times 0.055 =)$ 2.1 %. To remove time-varying demand shocks, column (2) absorbs shocks on the country*year

Table 11: **Real Effects** ***(firm-level)***

VARIABLES	(1) Δ long-term debt	(2) Δ long-term debt	(3) Δ employment	(4) Δ employment	(5) Δ investment	(6) Δ investment
banking crisis	-0.084***		-0.064***		-0.131***	
	(0.023)		(0.006)		(0.017)	
exposure	-0.269***	-0.261***	-0.155***	-0.074***	-0.242***	-0.163***
	(0.037)	(0.049)	(0.013)	(0.014)	(0.032)	(0.038)
exposure × BC	0.131***	0.105*	0.071***	0.029**	0.123***	0.119***
	(0.043)	(0.057)	(0.012)	(0.014)	(0.034)	(0.042)
Observations	53,574	49,340	51,445	47,496	54,638	51,845
R-squared	0.172	0.233	0.279	0.349	0.137	0.231
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Country*Year FE	-	Yes	-	Yes	-	Yes
Controls	-	Yes	-	Yes	-	Yes
Cluster	Firm	Firm	Firm	Firm	Firm	Firm

Note: This table shows regressions on the firm-year (firm) level. The dependent variables are log difference of firms' long-term debt, employment, and investment; *banking crisis (BC)* is a dummy with value one during banking crises in the firm country, as defined in Laeven and Valencia (2013); *exposure* is firms' exposure to diversified banks. *log total assets*, *return on assets*, and *leverage* are firm-level controls. For detailed variable definitions see Table 23 and text. All standard errors are clustered at the firm level. *** p<0.01, ** p<0.05, * p<0.1

level, column (3) on the more granular country*industry*year level.[28] In both specifications, coefficients are of similar sign, magnitude, and significance. In our preferred specification in column (3), moving a firm from the 25^{th} to 75^{th} percentile in terms of exposure to diversified banks leads to 1.5 % higher loan growth. Average loan growth equals 3.6 %, so the positive effect of borrowing from diversified banks is sizeable. The effect on the firm level is similar in size to effects on the loan level. This suggests that frictions hamper firms from switching across bank types during recessions, a common finding in the literature (Smith, Ongena and Smith, 2016; Cohen and Pascaline, 1997).

In Table 11 we restrict our sample to firms for which we have balance sheet information. To analyze real effects, we use long-term debt, employment, and investment as dependent variables (all in log differences). For each dependent variable, we run a parsimonious specification with firm fixed effects, as well as one enriched with time-varying firm controls and time-varying fixed effects at the country*year level.[29] We consistently find that firms borrowing from diversified banks have significantly higher growth rates during crises. In the more stringent specification, moving borrowers from the 25^{th} to 75^{th} percentile in terms of exposure to diversified banks leads to higher long-term debt (4.1 %, column (2)), employment (1.1 %, column (4)), and investment growth (4.6 %, column

[28] As *banking crisis* does not vary on the industry level, the coefficient is absorbed by fixed effects.

[29] Unfortunately, the low number of observations per industry leads to a large loss of observations when we use country*industry*year fixed effects.

(6)) during crises. Similar to loan growth in Table 10, growth rates are lower for high-exposure borrowers in normal times and fall during banking crises. This reflects that diversified banks lend to larger firms that have lower average growth rates (see Table 7). Controlling for common time-varying shocks on the country level as well as time-varying firm controls in general reduces the magnitude and significance of the effect.

Our loan- and firm-level findings show that firms can at most imperfectly substitute declines in syndicated lending by other forms of funding. Credit supply by diversified banks leads to real effects for firms. Results from Table 10 suggest that firms cannot switch from concentrated to diversified banks in the syndicated loan market. Otherwise, exposure in previous periods would not affect loan growth. The positive effects of exposure in Table 11 on long-term debt, as well as investment and employment, additionally indicate that firms cannot substitute from syndicated into non-syndicated lending. In sum, Tables 9−11 establish that changes on the syndicated loan market have real economic effects, which cannot be undone through other forms of credit. Borrowing from diversified banks significantly increases firms' loan growth during times of financial distress. In other words, diversified banks stabilize loan supply and smooth local financial shocks. In the following sections, we provide evidence that banks' diversification and internal capital markets explain our results.

3.2 Mechanism

Recent studies argue that diversified banks have better access to funding during times of financial distress and use their internal capital market to distribute resources among affiliates to smooth local shocks.[30] So far, our results do not tell us whether banks reallocate existing funds across affiliates, or raise new funds to sustain credit supply. The answer to the question has important implications, as the former implies spillover effects to unaffected markets, while the latter does not. Suppose there is a negative financial shock in Germany. Will a bank that is active in Germany and France move funds from France to Germany and reduce lending in France to prop up German affiliates? Or can it raise new funds, which allows it to stabilize lending in Germany while maintaining loan supply in France?

If diversification improves banks' access to funds in times of distress, it relaxes their 'financial constraints'. The additional funds could be raised in the crisis country, but also in unaffected borrower markets and transferred via the intra-bank capital market.

[30]See for example Morgan, Rime and Strahan (2004); Goldberg (2009); Cetorelli and Goldberg (2012); Buch and Goldberg (2014); Bord, Ivashina and Taliaferro (2018); Coleman, Correa, Feler and Goldrosen (2017); Cortés and Strahan (2017); Levine, Lin and Xie (2019).

'Constrained' non-diversified banks cannot raise new funds when they face a negative shock. Instead, they must trade off where to allocate existing liquidity within their bank network. Any reallocation of funds towards crisis countries will then lead to negative spillover effects to borrower markets that are connected to the bank. By analyzing changes in loan supply in connected countries, we thus can provide indirect evidence on banks' internal capital markets.

To answer the question we aggregate to the bank-borrower country-year level and define the variable *connected*. For each bank-country-year triplet, *connected* equals one for all non-crisis countries k ($\neq j$) in year t if country j has a crisis (where k and j sum up to all borrower countries from bank b in year t).[31] In the spirit of Giroud and Mueller (2015, 2017) the coefficient on *connected* shows how loan growth changes in all *connected countries* that borrow from bank b, but do not experience a crisis. We run regressions of the following form:

$$\begin{aligned}\Delta loan_{b,j,t} = \phi_{b,j} + \tau_t + \rho_1\ BC_{j,t} + \rho_2\ connected_{b,k,t} + \rho_3\ DIV_{b,t-1} \\ + \rho_4\ DIV_{b,t-1} \times BC_{j,t} + \rho_5\ DIV_{b,t-1} \times connected_{b,k,t} + u_{b,j,t},\end{aligned} \tag{4}$$

where the dependent variable is loan growth by bank b to all borrowers in j at t in log differences. DIV is our diversification metric on the bank level. We use bank-borrower country ($\phi_{b,j}$) and time (τ_t) fixed effects to analyze changes within a bank-borrower country connection and absorb common trends. We expect banking crises to affect loan growth negatively, so $\rho_1 < 0$. If there are spillover effects, connected markets see a fall in loan growth and $\rho_2 < 0$. From our previous results, we expect that diversified banks stabilize loan growth in host country j, so $\rho_4 > 0$. If diversified banks are financially unconstrained, they mitigate spillover effects and the coefficient on the interaction term ($DIV \times$ *connected*) is positive ($\rho_5 > 0$). In other words, if $\rho_5 > 0$ we conclude that diversified banks have better access to financing during host market shocks and transfer resources through their intra-bank capital market. We cluster at the bank level to account for serial and cross-sectional dependence across borrowers from the same bank. In all regressions, we include borrower-country macroeconomic controls trade (in % of GDP), inflation rate, log GDP per capita, and log population.

Table 12 shows that globally diversified banks have higher loan growth in crisis countries, and shield connected countries from spillovers. Column (1) shows that during banking crises, and in line with our previous findings, countrywide loan growth drops significantly by 3.0 %. Column (2) confirms for the aggregate level that diversified banks

[31] For example, for a bank that lends to Germany, France, and Italy, where Germany experiences a crisis in 2005, *connected* takes on value one for France and Italy in 2005 and zero otherwise.

are stabilizing, relative to banks with a concentrated portfolio. Similar to findings on the loan and firm level, the coefficient on diversification, interacted with banking crisis, is significant and positive. For banks with zero diversification, loan growth falls by 5.4 % during banking crises. Increasing diversification from the 25^{th} to the 75^{th} percentile attenuates the effect by $(0.63 \times 0.164 =)$ 4.1 %. Note that the highly significant coefficient on $DIV \times BC$ is equal in magnitude to the negative coefficient on banking crisis. This implies that banks with a fully diversified portfolio are able to completely offset the negative effect of a banking crisis on countrywide loan growth.

In column (3) we introduce our new variable *connected*. The negative and significant coefficient on *connected* implies that banks reduce lending by 2.9 % in unaffected countries when another borrowing country experiences a banking crisis. Note that the spillover effect is about two-thirds the size of the coefficient on banking crisis. Column (4) adds interaction terms. The positive and highly significant coefficients on $DIV \times BC$ and $DIV \times$ *connected* show that diversified banks stabilize loan supply in their host country, and reduce contagion effects. Moving a bank from the 25^{th} to the 75^{th} percentile reduces spillover effects from -6.3 % to zero. Fully diversified banks are thus able to offset the crisis-induced decline in loan supply both in affected and connected countries.

We interpret our results as evidence that being geographically diversified allows banks to tap new funds during crises, which reduces the need to withdraw capital from other markets. The ability to raise new deposits stabilizes banks' loan growth in the crisis country, but also shields connected markets from negative spillovers. This finding is in line with recent literature. Levine, Lin and Xie (2019) show that diversified banks have lower risk in their portfolio, which allows them to access cheaper funding during times of distress. Complementary, Cortés and Strahan (2017) find that banks use internal capital markets to reallocate funds towards regions with high loan demand. Similar to our findings, the reallocation has negative effects on connected areas for smaller and less diversified banks that cannot raise new funds. Bord, Ivashina and Taliaferro (2018) provide additional evidence that large and healthy banks raise new deposits to smooth shocks and shield connected markets from spillovers.

So far, our analysis focuses on the asset side of banks' balance sheets. We will now present direct evidence on the liability side to test the relationship between diversification and access to funding for a subsample of US banks. We merge 334 of our Dealscan banks with bank data provided by the FDIC's Statistics on Depository Institutions (SDI). For US banks, we obtain quarterly information on deposits, assets, return on assets, net interest margins, as well as Tier 1 capital, which results in a total of 6,446 bank-quarter

Table 12: **Spillover Effects** ***(bank-level)***

VARIABLES	(1) Δ loan vol.	(2) Δ loan vol.	(3) Δ loan vol.	(4) Δ loan vol.	(5) Δ loan vol.
banking crisis (BC)	-0.030***	-0.054***	-0.049***	-0.068***	-0.022*
	(0.005)	(0.008)	(0.006)	(0.009)	(0.012)
connected			-0.029***	-0.063***	-0.039***
			(0.006)	(0.012)	(0.014)
diversification (DIV)		-0.018		-0.034*	-0.042**
		(0.019)		(0.018)	(0.019)
DIV × BC		0.053***		0.052***	0.027
		(0.014)		(0.014)	(0.017)
DIV × connected				0.064***	0.061***
				(0.018)	(0.018)
Observations	167,213	167,213	167,213	167,213	166,976
R-squared	0.212	0.212	0.212	0.213	0.237
Bank*Borrower Country FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	-
Bank Country*Year FE	-	-	-	-	Yes
Controls	macro	macro	macro	macro	macro
Cluster	Bank	Bank	Bank	Bank	Bank

Note: This table shows regressions on the bank-firm country-year (bank) level. The dependent variable is log of total outstanding loan volume by bank b to all borrowers in country j; *banking crisis (BC)* is a dummy with value one during banking crises in the firm country, as defined in Laeven and Valencia (2013); *diversification (DIV)* is banks' portfolio diversification. *connected* is a dummy with value one when $BC = 1$ for all countries connected to bank b that are not country j and have no contemporaneous banking crisis. All regressions include borrower-country macroeconomic controls trade (in % of GDP), inflation rate, log GDP per capita, and log population. For detailed variable definitions see Table 23 and text. All standard errors are clustered at the bank level. *** p<0.01, ** p<0.05, * p<0.1

observations.[32] To see whether host country (non-US) shocks lead to an increase in deposits for diversified banks, we regress banks' log deposits on its diversification metric (DIV), interacted with the share of syndicated loans extended to crisis countries (*loans in crisis*). We control for size, Tier 1 capital ratio, return on assets, and net interest margin, as well as bank and quarter fixed effects. If diversified banks can tap new funds during times of distress, we expect a positive effect of diversification on US deposits.

Table 13 shows that diversified banks increase their deposits in response to a host country shock. Column (1) shows that for the average bank, deposits fall when it has a higher share of loans in distress. This could reflect that depositors question liquidity or solvency of the bank when parts of its loans are in distress. Once we add our interaction terms and controls in columns (2) and (3), we find that diversified banks increase their

[32]Dealscan and FDIC classify banks' parents by different criteria. With this caveat in mind, we match on subsidiary names, but assign each bank its parent's diversification value from Dealscan. SDI in general cover FDIC-insured depository institutions, which constitute most of the U.S. retail banking market. This leads to sample selection, as several banks in the syndicated loan market are not FDIC-insured.

Table 13: **FDIC SDI – Liability Side Mechanism**

VARIABLES	(1) log deposits	(2) log deposits	(3) log deposits	(4) log time dep.	(5) log demand dep.	(6) log money market dep.
loans in crisis	-0.640***	0.085	0.089	0.106	-0.243**	-0.138
	(0.212)	(0.058)	(0.066)	(0.099)	(0.107)	(0.268)
diversification (DIV)		0.240	0.228	0.016	0.255	0.435**
		(0.156)	(0.137)	(0.331)	(0.376)	(0.176)
DIV × loans in crisis		6.290**	6.340**	0.747	24.402***	11.786*
		(2.734)	(2.757)	(7.667)	(6.500)	(6.716)
Observations	6,446	6,446	6,446	6,074	6,021	5,909
R-squared	0.930	0.991	0.991	0.949	0.962	0.983
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	-	-	Yes	Yes	Yes	Yes
Controls	-	Yes	Yes	Yes	Yes	Yes
Cluster	State	State	State	State	State	State

Note: This table shows regressions on the bank-quarter level for FDIC SDI data (US banks only). The dependent variables are log deposits; *loans in crisis* is banks' share of loans extended to countries with a banking crisis, as defined in Laeven and Valencia (2013); *diversification (DIV)* is banks' portfolio diversification. All regressions include *log(assets)*, *tier 1 capital ratio*, *net interest margin*, and *return on assets* as bank-level controls. For detailed variable definitions see Table 23 and text. All standard errors are clustered at the US state level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

deposits during crises in borrower countries. Increasing diversification by one standard deviation leads to an increase in deposits of around 0.5 % (evaluated at the mean of share of loans in crisis). Thus, diversified banks raise new funds in their home market when faced with a shock in their host country. When we look at different types of deposits in columns (4)-(6), we see that the effect is driven by demand and money market deposits. Both types of deposits are short term and readily available, so it is reasonable to assume that banks cover their immediate needs following a crisis by raising short-term funding. There is no effect on time deposits (column (4)). While the sample covers only a limited number of US banks and has limited external validity, the strong positive effect of diversification on deposit growth supports our hypothesis that diversified banks can raise new funds during times of distress.[33]

4 Robustness

We argue that banks' geographic diversification is the reason that they stabilize loan supply. In this section we address potential alternative explanations. To ensure identification of supply effects, we run variants of loan-level regression Equation (2). In all

[33]Note that in columns (5)-(6) the coefficient on *share of loans in crisis* is negative. For concentrated banks, deposits fall in the US during host country shocks. A possible explanation is that they have to transfer existing funds to their affiliates in affected areas.

Table 14: **Foreign and International Banks**

VARIABLES	(1) log loan volume	(2) log loan volume	(3) log loan volume	(4) log loan volume	(5) log loan volume	(6) log loan volume	(7) log loan volume
diversification (DIV)		-0.002	0.005		-0.024	-0.116***	-0.102***
		(0.018)	(0.017)		(0.022)	(0.027)	(0.025)
DIV × BC		0.080***	0.077***		0.059***	0.067***	0.018
		(0.015)	(0.011)		(0.017)	(0.017)	(0.034)
foreign bank × BC	-0.016**	-0.044***	-0.019**				
	(0.008)	(0.011)	(0.009)				
DIV × foreign bank			0.006				
			(0.007)				
DIV × foreign bank × BC			-0.045***				
			(0.010)				
int. portfolio (INT)				0.047***	0.059***	0.011	0.023
				(0.013)	(0.018)	(0.022)	(0.023)
INT × BC				0.023**	-0.016	-0.026	-0.084***
				(0.012)	(0.017)	(0.016)	(0.024)
DIV × INT						0.158***	0.132***
						(0.036)	(0.035)
DIV × INT × BC							0.120**
							(0.059)
Observations	1,691,064	1,691,064	1,691,064	1,691,064	1,691,064	1,691,064	1,691,064
R-squared	0.976	0.976	0.976	0.976	0.976	0.976	0.976
Firm*Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm*Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster	Country*Year	Country*Year	Country*Year	Country*Year	Country*Year	Country*Year	Country*Year

Note: This table shows regressions on the bank-firm-year (loan) level. The dependent variable is log of total outstanding loan volume; *banking crisis (BC)* is a dummy with value one during banking crises in the firm country, as defined in Laeven and Valencia (2013); *diversification (DIV)* is banks' portfolio diversification. *foreign bank* is a dummy with value one if bank country and firm country differ. In column (3), *DIV* is a dummy with value 1 if a bank has above median diversification in a given year. *int. portfolio (INT)* is banks' portfolio share that is extended to foreign borrowers. For detailed variable definitions see Table 23 and text. All standard errors are clustered at the firm country-year level. *** p<0.01, ** p<0.05, * p<0.1

regressions, firm*bank and firm*time fixed effects absorb credit demand.

Foreign banks Diversified banks lend a significant share of their loans to foreign markets. A large literature finds that foreign and domestic banks differ during crisis episodes, which raises the concern that our classification by portfolio allocation simply reflects banks' nationality.[34] Table 14 shows that a categorization of banks by diversification is different from a categorization by nationality. We include a foreign bank dummy that takes on value 1 if a banks' home country is not equal to its host country.[35] Column (1) shows that foreign banks reduce lending by 1.6 % during host banking crises. Once we include our diversification metric in column (2), a non-diversified foreign bank reduces loan supply by 4.4 %. Diversified banks, on the other hand, are still stabilizing. Compared to baseline results in Table 9, the coefficient on $DIV \times BC$ increases in size to 8 % once we control for banks' nationality. This suggests that domestic banks with a diversified portfolio are the most stabilizing source of funding. We confirm this suspicion

[34] For a recent summary, see Claessens (2017).

[35] As nationality is constant within firm-bank connections, the coefficient on foreign bank is absorbed by fixed effects.

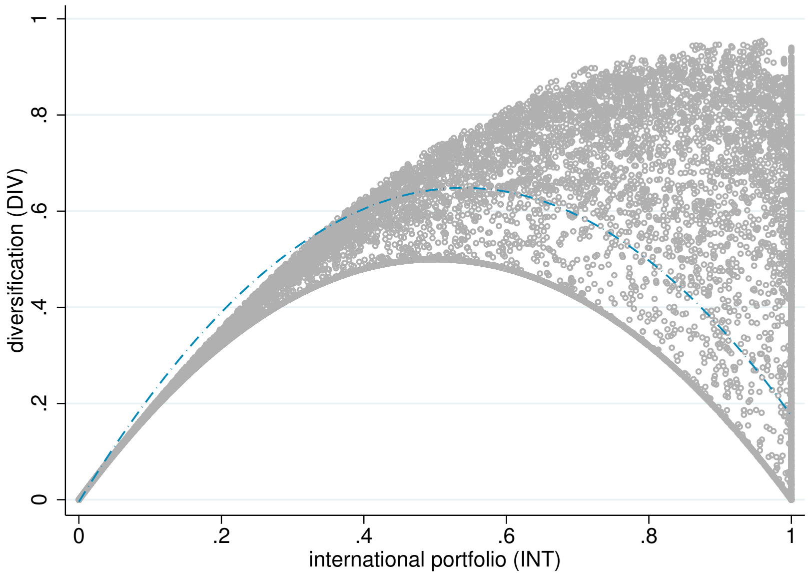
in column (3), where we interact the foreign dummy with diversification. For ease of interpretation we redefine *diversification* as a dummy with value one if diversification is above the yearly median. The interaction effect between diversification and foreign bank during banking crisis is highly significant and negative. The coefficients on interaction terms $DIV \times BC$ ($foreign\ bank \times BC$) remain positive (negative) and significant at the 1 % (5 %) level. In terms of economic significance, effects differ extensively across bank types. During banking crises, non-diversified foreign banks reduce lending by 1.9 %. Domestic diversified banks increase their relative loan supply by 8.2 %. The intermediate group of diversified foreign banks increases loan supply by 2.4 %. Results in columns (1)-(3) confirm the following pecking order: diversified domestic banks ($DIV = 1$, foreign bank = 0) are the most stable source of funding, while foreign banks with little diversification (DIV = 0, foreign bank = 1) are the most fickle. Foreign diversified banks lie in the middle. The ordering ties with findings on the flight home effect (Giannetti and Laeven, 2012) and behavior of gross capital flows during crises (Broner, Didier, Erce and Schmukler, 2013).

International loan portfolio The fact that banks extend international loans could itself reflect a different business model, regardless of diversification, and be responsible for our main findings. To take into account the international allocation of banks' loan portfolio, analogous to our diversification metric in Equation (1) we define banks' international portfolio as the ratio of international loans to total loans:

$$INT_{b,t} = \frac{intl.\ syndicated\ loan\ volume_{b,t}}{total\ syndicated\ loan\ volume_{b,t}} \in [0, 1]. \tag{5}$$

$Intl.\ syndicated\ loan\ volume_{b,t}$ is the sum of all loans by bank b in year t to firms located in a different country than the bank's parent entity. $Total\ syndicated\ loan\ volume_{b,t}$ is total lending in year t to all firms, domestic and foreign. We call banks with a low value of INT 'national', those with a high value 'international'. Figure 5 plots both metrics against each other, where international portfolio (INT) is on the x-axis, and banks' geographic diversification (DIV) on the y-axis (the blue line represents the quadratic fit). The humped shaped relationship that fans out for higher values of INT reflects the conceptual differences underlying each metric: banks that only lend domestically are in the bottom left corner (local on both metrics). Banks that lend exclusively to one foreign country are in the bottom right corner. They are globally integrated by our second definition (INT), but concentrated by our first (DIV), as they lend internationally but are

Figure 5: **Geographic Diversification and International Portfolio**



Note: This figure shows the relationship between banks' portfolio diversification (DIV) and the international allocation of their loan portfolio (INT) on the loan level. The blue dashed line is a quadratic fit. Higher values denote more portfolio diversification, and a higher share of loans extended to foreign borrowers, respectively. For detailed variable definitions see Table 23 and text.

not diversified.[36] The dispersion in diversification for a given level of 'internationality' indicates that banks lending internationally differ widely in the geographic allocation of their portfolio − being international does not automatically imply diversification. That being said, the correlation between both metrics is high (0.81).

Columns (4)-(7) in Table 14 show that diversification, not internationality, leads to positive loan supply effects. Column (4) shows that banks with a fully international portfolio stabilize loan growth by 2.3 %, significant at the 5 % level. However, once we include diversification in column (5), the positive effect disappears and turns negative, albeit insignificant. The positive stabilizing role of diversified banks remains. When we interact both metrics in columns (6) and (7), the following picture emerges. During banking crises, banks with international loans are stabilizing only if they have a diversified portfolio (positive coefficients on $DIV \times INT$ and $DIV \times INT \times BC$). Banks with a concentrated, but international, portfolio have a significant negative impact on loan

[36]The lower bound of the arch reflects the minimum level of diversification for each bank, given that it lends to more than one country. The upper bound, in turn, shows banks that lend to more than one country, but have a diversified (read: not geographically concentrated) portfolio.

TABLE 15: **Crisis Loans and Portfolio Risk**

VARIABLES	(1) log loan volume	(2) log loan volume	(3) log loan volume	(4) log loan volume	(5) log loan volume	(6) log loan volume
diversification (DIV)	0.001	0.002	-0.017	-0.025	-0.025	-0.024*
	(0.018)	(0.018)	(0.019)	(0.019)	(0.019)	(0.013)
DIV × BC	0.054***	-0.033	0.026**	0.047***	0.047***	0.037***
	(0.013)	(0.033)	(0.011)	(0.013)	(0.013)	(0.010)
share of loans in crisis	0.010	0.011				
	(0.014)	(0.014)				
BC × share of loans in crisis	0.032	-0.030				
	(0.020)	(0.033)				
DIV × BC × share of loans in crisis		0.099**				
		(0.041)				
portfolio risk (sales) × BC				-0.021***	-0.021***	
				(0.003)	(0.006)	
DIV × portfolio risk (sales) × BC					-0.002	
					(0.011)	
Observations	1,691,064	1,691,064	1,596,872	1,596,872	1,596,872	1,691,064
R-squared	0.976	0.976	0.974	0.974	0.974	0.990
Firm*Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm*Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank Size*Year FE	-	-	-	-	-	Yes
Cluster	Country*Year	Country*Year	Country*Year	Country*Year	Country*Year	Country*Year

Note: This table shows regressions on the bank-firm-year (loan) level. The dependent variable is log of total outstanding loan volume; *banking crisis (BC)* is a dummy with value one during banking crises in the firm country, as defined in Laeven and Valencia (2013); *diversification (DIV)* is banks' portfolio diversification. *share of loans in crisis* denotes banks' share of total loans extended to countries that suffer a banking crisis. *portfolio risk (sales)* is banks' portfolio risk, measured as the average standard deviation of borrowers' sales growth in non-crisis times. Column (6) includes time-varying fixed effects for quintiles of loan size (*Bank Size* Year FE*). For detailed variable definitions see Table 23 and text. All standard errors are clustered at the firm country-year level. *** p<0.01, ** p<0.05, * p<0.1

supply (coefficient of -0.084 on $INT \times BC$ in column (7)). We conclude that diversification, not banks' nationality, or whether they lend to foreign borrowers, explains the positive effects on loan supply during host country banking crises.

Share of loans in crisis An alternative explanation for our results is that diversified banks extend a smaller share of their total loan portfolio to countries in crisis. Once a banking crisis hits a borrower country, the asset side of a more diversified bank is less exposed to adverse effects such as loan write-downs. To test whether asset diversification is driving results we define for each bank *share of loans in crisis* as the share of total loans in year t that are extended to all borrower countries in crisis.[37] Diversified and concentrated banks have a similar average share of loans in crisis (32 %), but diversified banks' median share of loans in crisis is significantly higher (6.5 % to 1%).

In Table 15, column (1), we control for the share of loans in crisis, as well as its interaction with banking crisis. Our main coefficient of interest increases compared to

[37]For each bank b in year t, we define *share of loans in crisis*$_{t,b} = \frac{\sum_c BC_{t,c} L_{t,b,c}}{\sum_c L_{t,b,c}}$, where c denotes all countries borrowing from bank b in year t.

Table 16: **Firm Risk by Exposure to Diversified Banks *(firm-level sample)***

	high exposure		**low exposure**		**mean diff.**
	mean	sd	mean	sd	t
investment growth sd	0.54	(0.32)	0.62	(0.37)	10.63
employment growth sd	0.14	(0.10)	0.16	(0.12)	7.20
assets growth sd	0.18	(0.14)	0.20	(0.16)	6.87
sales growth sd	0.18	(0.12)	0.19	(0.14)	2.94
Observations	3689		3893		7582

Note: This table shows descriptive statistics on the firm-year (firm) level for the smaller sample of matched Compustat firms. *Risk* is defined as firms' standard deviation of investment/employment/asset7sales growth in non-crisis times. The sample is split by the yearly median according to firms' exposure. High exposure firms are denoted *high exposure*, those with low exposure as *low exposure*. *mean* denotes the mean, *sd* the standard deviation, and *mean diff.* the t-value for the difference in means across both groups. For detailed variable definitions see Table 23 and text.

our baseline loan-level regression (from 0.039 to 0.054). Hence the positive effect of diversification is not driven by the share of loans in crisis. For a given share of loans in distress, better diversification leads to higher loan supply. Once we introduce a triple interaction term in column (2), we see that a higher share of loans in crisis reduces loan volume for banks with no diversification. Instead, for a given share of loans in crisis countries, diversified banks stabilize loan volume, as indicated by the significant positive coefficient of $DIV \times share\ of\ loans \times BC$. The negative, but insignificant coefficient on DIV $\times$ BC could suggest that banks reduce lending to countries where they only hold a small share of loans. Diversification becomes more important for loan supply when a high share of loans is in distress.

Portfolio risk Banks differ in terms of borrower risk (Neuhann and Saidi, 2018; Levine, Lin and Xie, 2019). If diversified banks extend loans to less risky borrowers, they are less exposed to the negative effects of a crisis. To address this issue, for each bank we compute portfolio risk by taking the standard deviation of sales growth for each firm in non-crisis years. We consider non-crisis years only, as the stabilizing role of diversified banks during crises could lead to a downward bias in measured volatility. Table 16 shows that firms with low exposure to diversified banks are riskier in terms of volatility of investment, employment, asset, and sales growth. Firms are assigned into top and bottom tercile according to their exposure for each year.[38] In Table 15, column (3), we ensure that our baseline finding survives for the smaller sample of loans to borrowers with balance sheet information. Diversified banks still have significantly higher loan supply. Once we include portfolio risk (interacted with banking crisis) in column (4), we see that higher portfolio risk reduces loan supply during a banking crisis.[39] However, the main coefficient of interest on $DIV \times BC$ increases. Including a triple interaction effect in column (5) keeps the main coefficient stable. We also see that higher portfolio risk reduces loan supply for non-diversified banks. The positive triple interaction term indicates that for a given level of portfolio risk, better diversification leads to higher loan supply during crisis. We interpret this as evidence that portfolio risk is not responsible for the stabilizing effect we find, but that banks' diversification still leads to significantly higher loan supply during crises − in the presence of portfolio risk, the positive effect of diversification gains in importance.

Bank size Table 15, column (6) controls for bank size. As we have no direct data on bank size for the full sample, we assume that bigger banks grant larger loans and use loan size as proxy. To ensure that diversification has a positive effect on loan supply above and beyond banks' size, for each year we create quintiles by total loan volume. We then include size-quintile∗year fixed effects in our regression. We thus compare lending between each bank-firm pair within a given size class of banks in each year. We also include firm∗time fixed effects to absorb any change in loan demand. The positive and significant effect of diversification on loan supply survives once we control for banks' size. After including size*year fixed effects, during a banking crisis fully diversified banks have 3.7 % higher loan volume compared to non-diversified banks within the same size-year bin.

Industry Specialization It may be that geographic diversification can be explained by alternative dimensions of banks' business models. For instance, Boskovic, Doerr and Schaz (2019) provide evidence that banks stabilize lending to those industries in which they are specialized and thus have an informational advantage during banking crises. Table 17 tests whether the stabilizing effect of geographic diversification on lending can be explained by industry specialization. The last column in Table 17 shows that after controlling for industry specialization during crises, diversification remains positive and

[38]We restrict the analysis to observations for which we have balance sheet data, which reduces the number of loan-level observations by around 60 %.

[39]Portfolio risk is constant for banks and thus absorbed by fixed effects.

Table 17: **Geographic Diversification vs. Industry Specialization**

VARIABLES	(1) log loan volume	(2) log loan volume	(3) log loan volume
DIV × BC	0.072***		0.068**
	(0.027)		(0.028)
Industry spec. × BC		-0.021	-0.014
		(0.054)	(0.056)
Industry spec.		1.742***	1.740***
		(0.047)	(0.047)
Observations	1,621,124	1,621,124	1,621,124
R-squared	0.978	0.978	0.978
Firm*Bank FE	Yes	Yes	Yes
Firm*Year FE	Yes	Yes	Yes
Country*Industry*Year FE	-	-	-
Bank*Year FE	Yes	Yes	Yes
Cluster	Country*Year	Country*Year	Country*Year

Note: This table shows regressions on the bank-firm-year (loan) level. The dependent variable is log of total outstanding loan volume; *banking crisis (BC)* is a dummy with value one during banking crises in the firm country, as defined in Laeven and Valencia (2013); *diversification (DIV)* is banks' geographic diversification. *Industry specialization* is measured as the ratio of loans granted by bank b to all borrowers in industry i in time period t relative to bank b's total lending granted in the same period. For detailed variable definitions see Table 23 and text. Standard errors are clustered on different level, as indicated by the last table row. *** p<0.01, ** p<0.05, * p<0.1

statistically significant.[40] This suggests that lending by geographically diversified banks during banking crises cannot be explained by banks' industry specialization.

Clustering Table 18 shows that our results are robust to clustering standard errors on different levels. Column (1)-(4) cluster on the country*year, country, country and bank, as well as firm*year and bank*year level. Across specifications, the effect of diversification on loan supply during crises remains significant at the 5 % top 1 % level.

[40]Note, that the coefficient of the interaction term between industry specialization and banking crises is not statistically different from zero while it is positive in Boskovic, Doerr and Schaz (2019). The reason is that the sample of banks differs as we now include not only lead arrangers, as in Boskovic, Doerr and Schaz (2019), but also participant banks of the syndicate. However, as participant banks are not in direct contact with the borrower they are not able to gather soft information over the industry by issuing loans. Hence, industry specialization on this sample does not capture informational advantage over industries.

Table 18: **Bank-firm level − cluster**

VARIABLES	(1) log(loan vol)	(2) log(loan vol)	(3) log(loan vol)	(4) log(loan vol)
diversification (DIV)	0.005	0.005	0.005	0.005
	(0.018)	(0.051)	(0.055)	(0.016)
DIV × BC	0.039***	0.039**	0.039**	0.039***
	(0.013)	(0.016)	(0.018)	(0.014)
Observations	1,691,064	1,691,064	1,691,064	1,691,064
R-squared	0.976	0.976	0.976	0.976
Firm*Bank FE	Yes	Yes	Yes	Yes
Firm*Year FE	Yes	Yes	Yes	Yes
Cluster	Country*Year	Country	Country & Bank	Firm*Year & Bank*Year

Note: This table shows regressions on the bank-firm-year (loan) level. The dependent variable is log of total outstanding loan volume; *banking crisis (BC)* is a dummy with value one during banking crises in the firm country, as defined in Laeven and Valencia (2013); *diversification (DIV)* is banks' geographic diversification. For detailed variable definitions see Table 23 and text. Standard errors are clustered on different level, as indicated by the last table row. *** p<0.01, ** p<0.05, * p<0.1

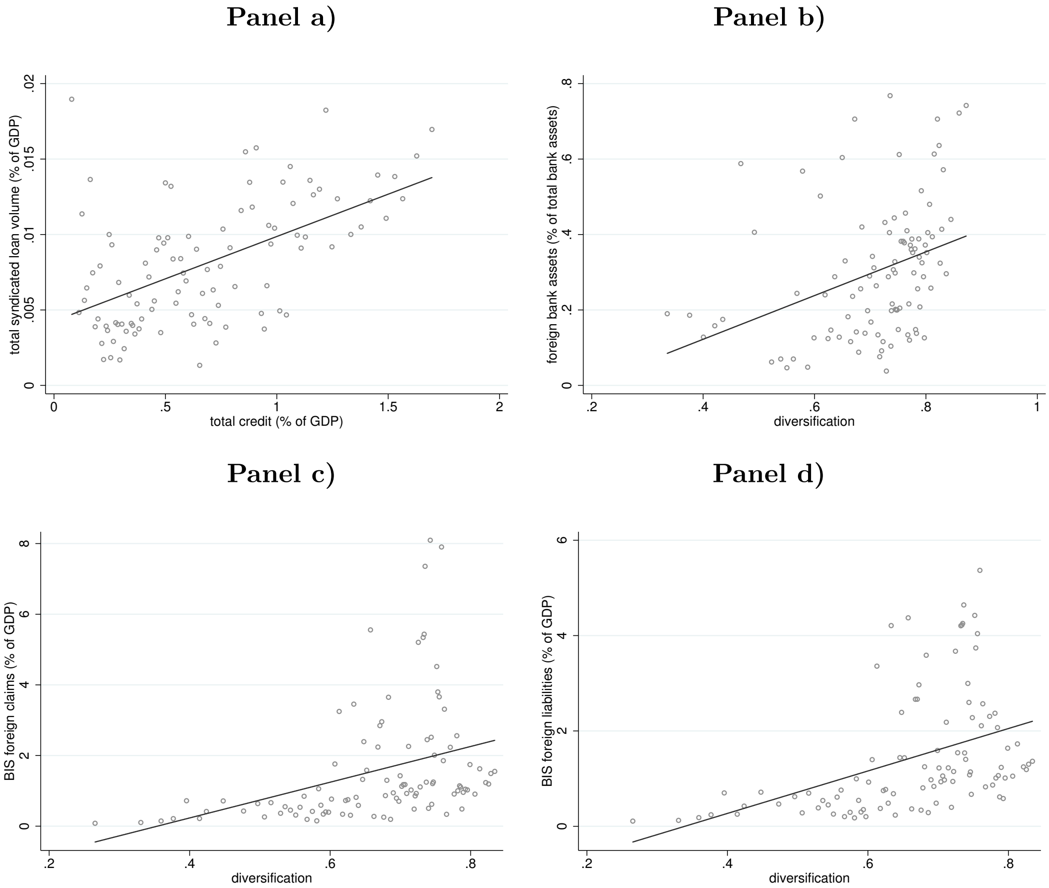
5 Extensions

This section presents extensions and further robustness checks of our baseline findings. We show that our diversification metric correlates with macro variables of financial integration; effects are stronger for financially constrained firms; diversified banks extend loans at longer maturity, but higher interest during crises; and that, following a crisis, there is a shift in firms' portfolios towards lending by diversified banks.

Macro evidence We use syndicated loan market data to construct our bank diversification metric. Syndicated lending represents a sizable share of firm debt and cross-border loans (Gadanecz and von Kleist, 2002). We now show that our metric (aggregated to the country level) correlates with aggregate country-level variables. Figure 6, Panel a) shows a strong positive relationship between borrowing countries' total syndicated lending (as share of GDP) against total credit (as share of GDP). Countries with a high level of overall credit also have a high level of syndicated loan volume.[41] Panels b)−d) show the relationship between our diversification metric and aggregate measures of banking integration. Diversification is positively correlated with the share of foreign bank assets (as

[41] A regression of total credit on syndicated credit with country fixed effects yields a coefficient of 0.29 with t-value 11.47.

FIGURE 6: **Macro Evidence**



Note: This figure shows the relationship between our sample data and aggregate data on total credit, as well as our diversification metric and aggregate measures of financial integration. All scatter plots depict scatter points as well as a linear fit, where the underlying data is aggregated to the country-year level. For detailed variable definitions see Table 23 and text.

share of total bank assets), claims by foreign banks, as well as foreign liabilities (both as share of GDP).[42] Hence, countries with a high share of firms borrowing from diversified banks are also better financially integrated. They have higher foreign bank presence in their domestic market, as well as larger claims on foreign countries. Taken together, this implies that syndicated lending in our data is positively correlated with total credit, and our diversification metric captures financial integration.

[42] Data is provided by the Bank for International Settlements, the World Bank World Development Indicators, as well as Global Financial Development Database. See Table 23 for details.

Table 19: **Financial Constraints *(firm-level sample)***

VARIABLES	(1) uncons. payout Δ employment	(2) cons. payout Δ employment	(3) uncons. size Δ employment	(4) cons. size Δ employment	(5) uncons. payout Δ investment	(6) cons. payout Δ investment	(7) uncons. size Δ investment	(8) cons. size Δ investment
exposure	-0.055*	-0.103***	-0.033	-0.033	0.024	-0.265***	-0.075	-0.106
	(0.029)	(0.032)	(0.024)	(0.024)	(0.080)	(0.083)	(0.067)	(0.079)
exposure × BC	-0.003	0.094***	0.063	0.041*	-0.058	0.277**	-0.077	0.201**
	(0.024)	(0.033)	(0.041)	(0.025)	(0.072)	(0.109)	(0.134)	(0.084)
Observations	11,347	12,207	15,598	15,433	12,017	12,808	16,742	16,660
R-squared	0.336	0.472	0.333	0.413	0.272	0.317	0.249	0.260
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country*Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster	Firm	Firm	Firm	Firm	Firm	Firm	Firm	Firm

Note: This table shows regressions on the firm-year (firm) level. The dependent variables are log difference of firms' employment and investment; *banking crisis (BC)* is a dummy with value one during banking crises in the firm country, as defined in Laeven and Valencia (2013); *exposure* is firms' exposure to diversified banks. All regressions include *log total assets*, *return on assets*, and *leverage* as firm-level controls. *uncons.* and *cons.* denote constrained and unconstrained firms, split into bottom and top tercile of payout ratio or size for each year. For detailed variable definitions see Table 23 and text. All standard errors are clustered at the firm level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Financial constraints We split firms into financially constrained and unconstrained. As constrained firms rely more on external credit to finance employment and investment, higher exposure to diversified banks should have stronger effects. For each year we group firms into bottom and top tercile according to their payout ratio (*payout*) and size (*size*). We classify firms as financially constrained if they are in the bottom tercile, and unconstrained if they are in the top tercile (Almeida and Campello, 2007; Chaney, Sraer and Thesmar, 2012). In Table 19, columns (1)-(4) use employment growth as dependent variable, columns (5)-(8) investment growth. All regressions include baseline controls, as well as firm and country*year fixed effects. For both dependent variables, the positive effect of exposure to diversified banks during crises is significantly stronger for constrained (*cons.*) than unconstrained (*uncons.*) firms. Note that our Compustat sample covers large and listed firms. The stronger effects for financially constrained firms reassure us that effects would extend to a sample covering small firms as well. In general, small firms are found to be more bank dependent and also more credit constrained and therefore loan supply decisions matter more.

Maturity and interest rates Beside changes in loan amount, banks can alter maturity or the interest rate of loans. To test whether banks use these margins to restrict or expand loan supply, we rerun firm level regression Equation (3), but replace the dependent variable by *maturity* (in months), and *interest spread* over LIBOR (in basis points). Table 20 shows that borrowing from diversified banks leads to a higher spread

Table 20: **Maturity and Sample Selection** ***(firm-level sample)***

VARIABLES	(1) loan spread	(2) maturity	(3) 1995-2008 Δ loan volume	(4) GFC Δ loan volume	(5) regional crisis Δ loan volume
exposure	-35.486***	6.392***	-0.249***	-0.186***	-0.182***
	(6.932)	(1.763)	(0.027)	(0.022)	(0.022)
exposure × BC	30.816***	2.636	0.070***	0.057***	0.054**
	(6.288)	(1.899)	(0.023)	(0.022)	(0.022)
exposure × GFC				0.066**	
				(0.025)	
exposure × GFC × BC				-0.100***	
				(0.031)	
exposure × regional BC					-0.029*
					(0.018)
Observations	139,505	199,799	133,542	196,038	196,038
R-squared	0.905	0.951	0.338	0.317	0.317
Firm FE	Yes	Yes	Yes	Yes	Yes
Country*Industry*Year FE	Yes	Yes	Yes	Yes	Yes
Cluster	Firm	Firm	Firm	Firm	Firm

Note: This table shows regressions on the firm-year (firm) level. The dependent variable is firms' average *loan spread* over LIBOR (in basis points) and *maturity* (in months) in columns (1) and (2), and log difference of firms' total outstanding loan volume in columns (3)-(5); *banking crisis (BC)* is a dummy with value one during banking crises in the firm country, as defined in Laeven and Valencia (2013); *exposure* is firms' exposure to diversified banks. *Great Financial Crisis (GFC)* is a dummy with value one during banking crises from 2008-2010. *regional crisis* is a dummy with value one during regional banking crises in Asia, Latin America, and Europe. For detailed variable definitions see Table 23 and text. All standard errors are clustered at the firm level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

and longer maturity during crises. While the effect on maturity is quantitatively negligible and insignificant, a one standard deviation increase in exposure increases the spread by around 7 basis points. We interpret this as evidence that diversified banks are willing to extend loans during crises, but compensate higher risk through higher interest rates. Columns (3)-(5) further examine the robustness of our results. The dependent variable is loan growth. Column (3) excludes the global crisis and restricts the sample to years $1995-2008$. Column (4) introduces a global financial crisis (GFC) dummy with value one during banking crises in years 2008, 2009, and 2010. In both columns, our main effect remains positive and significant. The recent financial crisis does not drive our results. Finally, column (5) introduces a regional crisis dummy.[43] The negative coefficient on $exposure \times regional\ BC$ suggests that during crises affecting several countries at once, the positive effect of diversification is weakened. Yet, our baseline effect remains stable.

[43]The *regional BC* dummy takes on value one for Asian countries during the Asian crisis (1997-1999), South American countries during the Latin crisis (1995-1996), as well as the Great Financial Crisis in Europe and the US.

Table 21: **Substitution Towards Diversified Lenders**

VARIABLES	(1) firm t exposure	(2) firm t+1 exposure	(3) firm t+2 exposure	(4) firm t+3 exposure	(5) industry t exposure	(6) industry t+1 exposure	(7) industry t+2 exposure	(8) industry t+3 exposure
banking crisis	0.007***	0.006**	0.010***	0.007**	0.003	0.005	0.012***	0.011***
	(0.002)	(0.002)	(0.002)	(0.003)	(0.004)	(0.004)	(0.004)	(0.004)
Observations	192,495	155,610	123,045	98,076	192,495	159,703	127,892	101,469
R-squared	0.924	0.926	0.928	0.928	0.505	0.497	0.489	0.485
Firm FE	Yes	Yes	Yes	Yes	-	-	-	-
Country*Industry FE	-	-	-	-	Yes	Yes	Yes	Yes
Region*Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster	Firm	Firm	Firm	Firm	Firm	Firm	Firm	Firm

Note: This table shows regressions on the firm-year (firm) level. The dependent variable is firms' exposure to diversified banks (the share of total loans extended by diversified banks), where we lead the dependent variable by up to 3 periods. *banking crisis (BC)* is a dummy with value one during banking crises in the firm country, as defined in Laeven and Valencia (2013). Columns (1)-(4) use firm fixed effects and look at within firm variation, columns (5)-(8) use country-industry fixed effects and look at changes across firms within industries. For detailed variable definitions see Table 23 and text. All standard errors are clustered at the firm level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Credit Substitution Effects While we showed above that diversified banks sustain higher loan supply and credit growth to firms during crises, we now investigate how the differing behavior of diversified and concentrated banks changes the structure of the economy. First, we look at substitution effects on the firm level. While firms cannot perfectly offset changes in loan supply by switching across banks, Table 21 shows that there is nonetheless an increase in reliance on diversified lenders. We run a regression of firms' exposure (i.e. the share of loans coming from diversified banks) on the banking crisis dummy. Columns (1)-(4) use firm and region*year fixed effects, and look at within firm changes, while controlling for common regional shocks. All regressions include firm-country controls trade, inflation, log GDP per capita, and log population. There is a significant and positive effect of banking crisis on firms' exposure. The average firm sees an increase in its exposure to diversified lenders by 0.7 % during the year of the crisis. Effects are highly persistent even three years after the crisis. Besides a shift in exposure within firms, there could also be a shift across firms towards firms that borrow more from diversified banks. Columns (5)-(8) use country*industry instead of firm fixed effects and compare how exposure changes across firms within a given country-industry pair. Results show that during a banking crisis there is a shift towards borrowers from diversified banks. The share of loans from diversified banks increases by 0.3 % in the year of the crisis. It is still 1.1 % higher three years after the crisis. The stronger effect on the industry level suggests that on top of a shift towards diversified lenders *within* firms, there is also a shift within industries *across* firms towards borrowers with higher exposure.

The increase in firms' reliance on diversified banks should be mirrored in banks' loan portfolios. We run the following regression on the bank (b) − borrower country (j) − year (t) level:

$$share_{b,j,t} = \gamma_1 BC_{j,t} + \gamma_2 diversification_{b,t} + \gamma_3 DIV_{b,t} \times BC_{j,t} + X_{j,t} + \epsilon_{b,j,t}.$$

$share_{b,j,t}$ denotes bank b's share of total loans in country j in year t and X is a set of controls for the borrower country. Based on our above findings, we expect that a banking crisis leads to a decline in $share$ ($\gamma_1 < 0$), but the decline should be smaller or absent for diversified banks ($\gamma_3 > 0$), as they are a more stable source of funding. The coefficient γ_2 on DIV is expected to be negative, as diversified banks will have a lower average loan share than concentrated banks. In each regression, we use bank*borrower country fixed effects and analyze variation in loan shares within a specific bank-borrower country connection. We also employ time-varying fixed effects on the bank country level to absorb changes in each banks' home country. If, for example, there is a contemporaneous negative shock in a banks' home country that we do not account for, the stabilizing effect of diversification is likely to be muted. Again, all regressions include borrower-country controls trade, inflation, log GDP per capita, and log population.

Table 22, column (1), shows that a banking crisis in host country j reduces banks' share of loans extended to j by 0.7 %. The effect is significant at the 1 % level and economically meaningful. The median loan share is 2.2 %, so a banking crisis reduces banks' loan share by around 31 % relative to the median. Once we interact our crisis dummy with our diversification metric in column (2), we see that *i)* in non-crisis times, diversified banks have a lower loan share in host countries than concentrated banks; and *ii)* their share falls by less during banking crises. Columns (2)-(5) lead the dependent variable by subsequent periods. In each specification we find that diversified banks reduce their loan share by less. For example, in column (2), fully diversified banks reduce their loan share by 0 %, compared to 1.3 % for banks with no diversification. Combining our evidence in Tables 21 and 22, we find that banking crises in host countries increase borrowers' reliance on lending by diversified banks. The long-run effects of the increase in importance of diversified banks on financial stability and, for example, spillover effects, is an interesting question for future research.

Table 22: **Dynamics: Diversified Banks Increase their Loan Share**

VARIABLES	(1) t share	(2) t share	(3) t+1 share	(4) t+2 share	(5) t+3 share
banking crisis (BC)	-0.007***	-0.013***	-0.012***	-0.010***	-0.010***
	(0.002)	(0.004)	(0.004)	(0.003)	(0.003)
diversification (DIV)		-0.310***	-0.198***	-0.125***	-0.067***
		(0.013)	(0.011)	(0.010)	(0.010)
DIV × BC		0.013***	0.008*	0.005	0.003
		(0.005)	(0.005)	(0.004)	(0.005)
Observations	199,427	173,368	149,664	127,568	109,366
R-squared	0.959	0.967	0.968	0.970	0.971
Bank*Borrower Country FE	Yes	Yes	Yes	Yes	Yes
Bank Country*Year FE	Yes	Yes	Yes	Yes	Yes
Cluster	Bank	Bank	Bank	Bank	Bank

Note: This table shows regressions on the bank-firm country-year (bank) level. The dependent variable is banks' share of total outstanding loan volume extended to all borrowers in country j, up to a lead of three years; *banking crisis (BC)* is a dummy with value one during banking crises in the firm country, as defined in Laeven and Valencia (2013); *diversification (DIV)* is banks' portfolio diversification. For detailed variable definitions see Table 23 and text. All standard errors are clustered at the bank level. *** p<0.01, ** p<0.05, * p<0.1

6 Conclusion

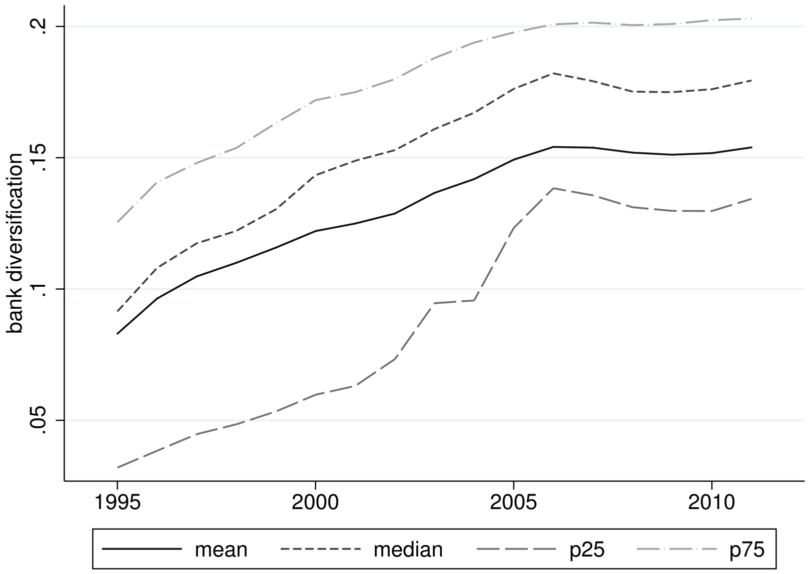
We develop a novel metric to categorize banks according to the geographic diversification of their international loan portfolio. For a large sample of international syndicated loans, we find that diversified banks are a resilient source of financing for firms that experience a countrywide financial crisis. Borrowing from diversified banks increases loan, investment, and employment growth significantly. Detailed loan-level data ensures proper identification of supply effects, as we absorb changes in firm demand through time-varying fixed effects on the firm level. Our results provide evidence that diversification allows banks to raise new funds during times of distress, which are then allocated towards affiliates in distress. This not only stabilizes loan supply in affected countries, but also reduces spillover effects to connected markets.

When we contrast our measure with the standard classification by nationality, we find that domestic, diversified banks are the most resilient source of financing, while foreign banks provide no insurance. The negative effect of foreign banks is increasing in the concentration of their portfolio. We also exclude candidate explanations other than diversification. Geographic diversification remains a significant factor contributing to higher stability in lending even after we control for banks' international orientation, share of loans in crisis, and portfolio risk.

This paper contributes to the debate on the costs and benefits of financial integration. Figure 7 shows that banks' diversification declined during the global financial crisis and remained depressed thereafter. Our results suggest that the recent retrenchment in financial integration following the Great Financial Crisis is worrisome (Milesi-Ferretti and Tille, 2011; Cerutti and Claessens, 2016; Claessens and Van Horen, 2015). While cross-border lending constitutes a potential source of contagion, we show that internationally active and diversified banks have better access to funds during banking crises in their borrower countries and increase resilience to local shocks.

7 Appendix

FIGURE 7: **Banks' Geographic Diversification Over Time**



Note: This figure shows the change in banks' diversification over time. Diversification is computed according to Equation (1). It plots the mean, median, 25^{th}, and 75^{th} percentile from 1995 to 2012. Diversification increased steadily until around 2006, but then decreased during the recent global financial crisis and remains depressed ever since. Less-diversified banks drive the decline. For detailed variable definitions see Table 23 and text.

Table 23: **Variable Definitions**

variable	**description/item**	**unit/comment**
loan volume	outstanding syndicated loans	million
loan spread	interest spread over LIBOR	basis points
maturity	loan maturity	months
banking crisis (BC)	banking crisis in borrower country	dummy
connected	connected countries with no contemporaneous banking crisis	dummy
diversification (DIV)	diversification index	[0,1-1/J], bank level
exposure	firm exposure to diversified banks	[0,1-1/J], firm level
investment ratio	capx/ppent$_{t-1}$ (CS)	%
long-term debt ratio	dltt/at (CS)	%
employment	emp (CS)	thousand
sales	sale (CS)	million
assets	at (CS)	million
return on assets (ROA)	(opid - depam)/at (CS)	%
sales growth	ln(sale$_t$) - ln(sale$_{t-1}$) (CS)	%
payout ratio	(dvt + prstkc)/oibdp (CS)	%
fixed assets	ppe (CS)	million
capital-labor ratio	ppe/emp (CS)	%
foreign bank (FB)	borrower country $\neq$ lender country	dummy, bank level
international portfolio (INT)	int. loan volume to total loan volume	[0,1], bank level
great financial crisis (GFC)	years 2008-2010	dummy
regional BC	regional banking crisis for Asia, Latin America, Europe, and US	dummy
home BC	banking crisis in lender country	dummy, bank level
share of loans in crisis	share of syndicated loans extended to crisis countries in year t	%
portfolio risk (sales)	standard deviation of borrower sales growth in non-crisis times	
credit to GDP	FD.AST.PRVT.GD.ZS (WB WDI)	%
BIS foreign claims	total cross-border claims (BIS CBS)	%
BIS foreign liabilities	total cross-border liabilities (BIS CBS)	%
foreign bank assets	as share of total bank assets (WB GFDD)	%

Note: CS stands for Compustat, WB for World Bank, GFDD for Global Financial Development Database, WDI for World Development Indicators, BIS for Bank for International Settlements, CBS for Consolidated Banking Statistics.

FIGURE 8: **Bank-Borrower Connections**

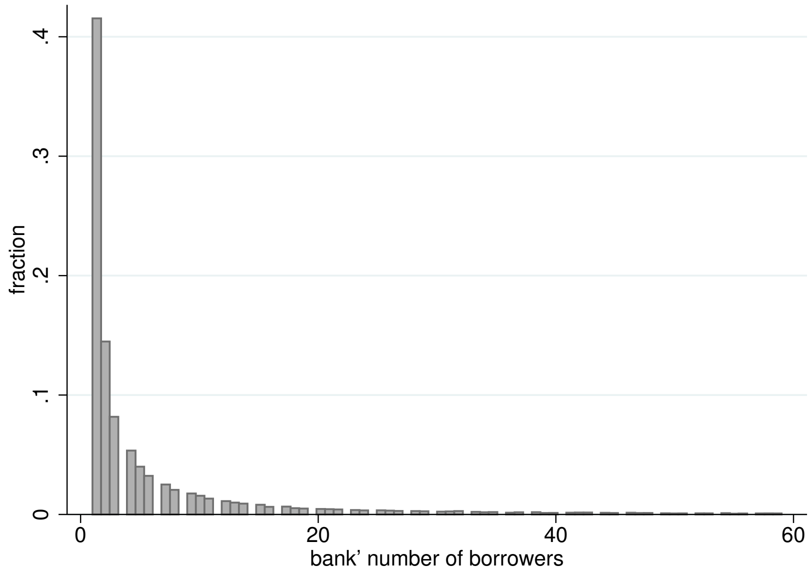
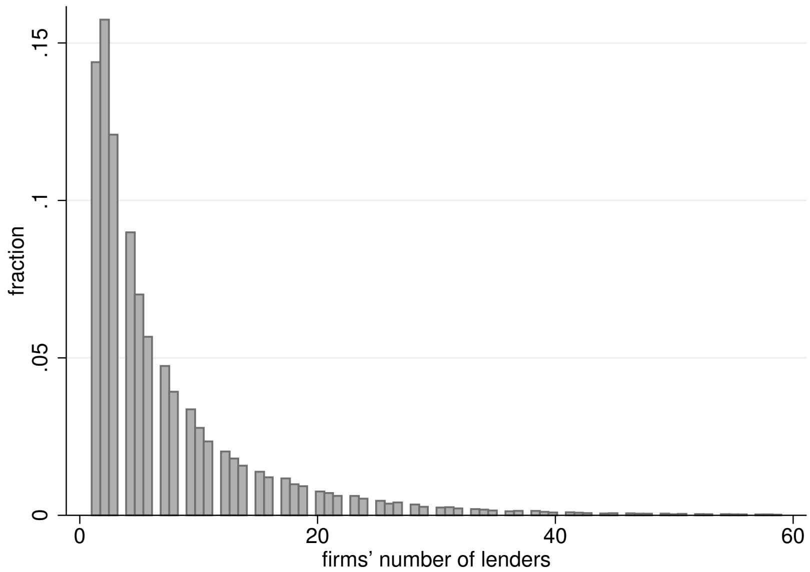
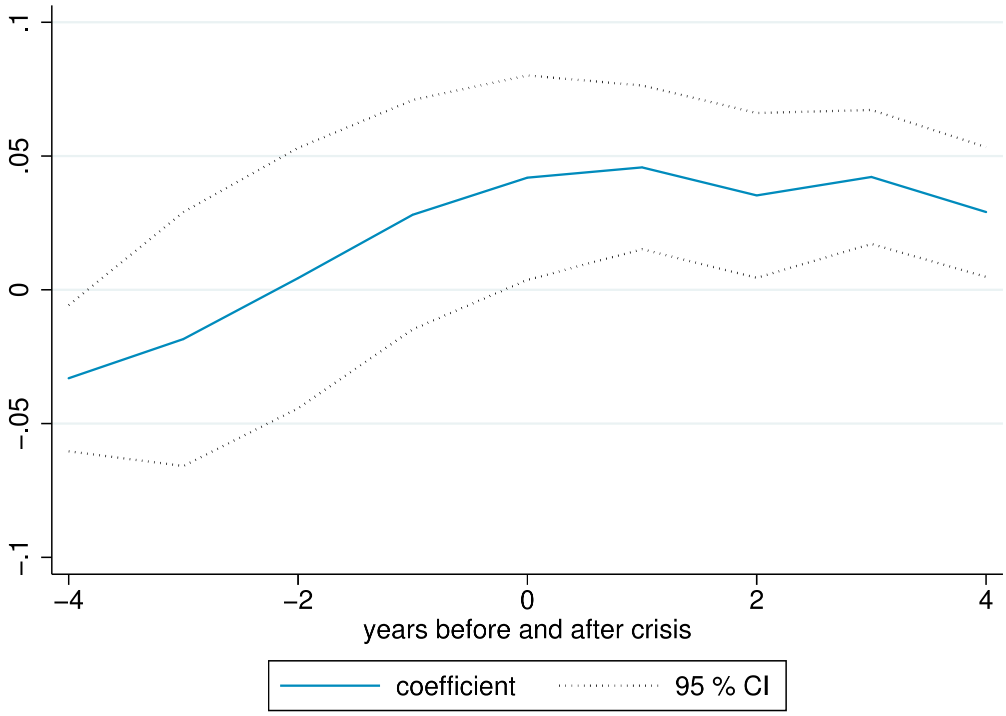


FIGURE 9: **Firm−Lender Connections**



Note: This figures shows the number of distinct borrowers in each year for each bank (top panel) and the number of distinct lenders in each year for each firm (bottom panel). For visibility, graphs are truncated at 60 connections.

Figure 10: **Loan Supply Over Time**



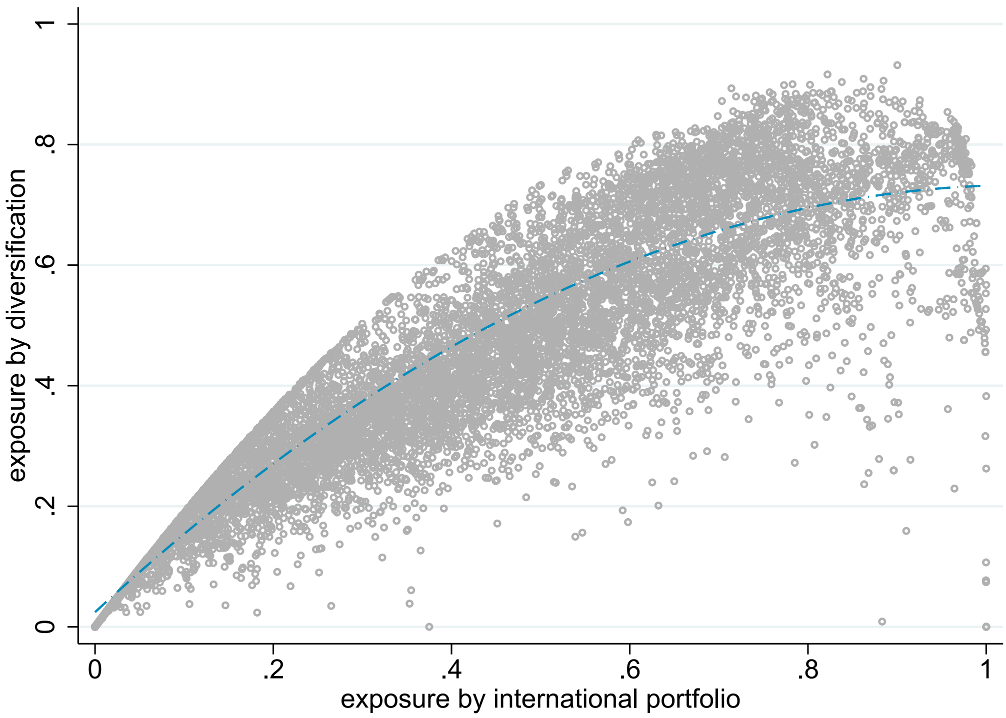
This figure shows the coefficient and corresponding confidence intervals (CI) of a regression of log loan volume on diversification, which we interact with time dummies for the years before, during, and after the crisis. While there is no significant difference in loan supply prior to the crisis, diversified banks maintain significantly higher loan supply during and after the crisis.

Table 24: **Foreign Banks**

VARIABLES	(1) concentrated log loan volume	(2) diversified log loan volume	(3) full sample log loan volume
foreign bank × BC	-0.031***	-0.087***	-0.015
	(0.008)	(0.011)	(0.010)
diversification (d)			-0.028***
			(0.009)
DIV (d) × BC			0.087***
			(0.012)
DIV (d) × foreign bank			0.034***
			(0.012)
DIV (d) × foreign bank × BC			-0.054***
			(0.011)
Observations	807,188	801,124	1,691,064
R-squared	0.985	0.971	0.976
Firm*Bank FE	Yes	Yes	Yes
Firm*Year FE	Yes	Yes	Yes
Cluster	Country*Year	Country*Year	Country*Year

Note: Table 24, columns (1)-(3) shed further light on the distinction between foreign and diversified banks. Whether you are diversified or not, you want to have a domestic bank during a local crisis. Foreign banks reduce their loan volume by significantly more. Interestingly, foreign banks with a diversified portfolio reduce their loan volume by 8.7 % more than foreign banks with a concentrated portfolio. This is almost triple the difference between foreign and domestic banks that have a concentrated portfolio. So if you can choose, you want to be diversified, but domestic. Column (3) confirms this with an interaction regression of the foreign bank dummy and a dummy for banks with high and low diversification. The most stably source of funding are domestic diversified banks, the least stable source of funding foreign banks with no diversification. For detailed variable definitions see Table 23 and text. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

FIGURE 11: **Firm Exposure to Divsersified Banks *(firm-level sample)***



Note: This figure shows the relationship between firms' exposure to diversified banks (DIV) and international banks (INT) on the firm level. The blue dashed line is a quadratic fit. Higher values denote higher exposure to the respective bank type. For detailed variable definitions see Table 23 and text.

Chapter II

Bank Industry Specialization and Spillover Effects

Based on Boskovic, Doerr and Schaz (2019).

1 Introduction

The recent financial crisis led to a substantial rebalancing of banks' international loan portfolios. Some banks cut lending to crisis countries and moved their funds back home, others shifted their loan portfolio towards other countries.[1] While many researchers have analyzed the role that geographical specialization plays for credit reallocation after a funding shock during a banking crisis, very few have focused on the impact of other types of bank portfolio concentration, such as concentration by industry. This is surprising, given the important role that bank's portfolio concentration plays in theoretical banking models and given the severe consequences that credit reallocation after a banking crisis might have for the real economy (De Jonghe et al., 2016).[2]

Previous literature established that banks specialize in certain industries to acquire an informational advantage. Soft information about borrowers in their main industries allow them to better gauge the quality of a firm during times of general economic distress. When engaging in relationship lending, banks gather propriety information about their customers through repeated interactions (Boot, 2000). Banks will typically have gathered more sector-specific knowledge in sectors where they are specialized, improving their screening abilities and reducing the need for costly monitoring in these sectors. As such,

[1]See (Giannetti and Laeven, 2012); (Cetorelli and Goldberg, 2011); (Giroud and Mueller, 2017); (Popov and Van Horen, 2015) for evidence of domestic and international loan portfolio relocation of banks.

[2]See (Beck et al., 2017); (Degryse and Ongena, 2007); (Jahn et al., 2016); (Giannetti and Saidi, 2019); for evidence and implications of bank portfolio concentration.

while banks that face a funding shock during a banking crisis are forced to reduce lending, they have an incentive to shield sectors in which they are specialized and have relatively superior screening and monitoring skills (De Jonghe et al., 2016). Yet, despite these considerations, it remains an open question whether funding shocks lead to differential reallocation effects in bank portfolios across industries, depending on banks' ex-ante specialization to these industries. Therefore, we address following questions: Do banks protect borrowers in their main industries during banking crises in order to maintain this valuable information for the post-crisis period? Or does industry specialization allow banks to discriminate more easily between good and bad firms in their main industry, which allows them to cut lending more strongly to main-industry-firms leading to a stronger lending contraction during a crisis?

This paper looks at how banks' industry specialization affects lending during a banking crisis in the borrower country. On the bank-firm (loan) level, we find that banks mitigate the transmission of the banking crisis by reducing lending less to firms in their specialized industries. Increasing bank's industry specialization by one standard deviation increases loan volume to firms in these industries by 6.3 % during banking crises. We document a positive relationship between bank specialization and firm lending: Banks reduce lending strongest to firms from their least specialized industries. Firms within the bottom tercile of bank specialization experience a fall in loan supply that is 8 % stronger than for firms from the middle tercile. On the bank-industry level, we find that banks protect their specialized industries on aggregate, rather than cherry-pick firms within a specialized industry they know well.

We find that the positive loan supply effect to firms in specialized industries compared to firms in non-specialized industries during crises has real effects on industry wide employment and growth. To test this, we construct a variable that measures exposure of a particular industry to specialized banks. Industries that receive more lending from banks that are specialized in this particular industry, have more stable economic outcomes during banking crises. While industry level employment falls on average by 5 % during a crisis, increasing industry exposure to specialized banks by one standard deviation mutes this reduction by 2.8 %. Additionally, the reduction of industry specific value added is muted by 1.7 % for a similar increase in industry exposure to specialized banks.

In a second step of our research, we analyze how banking crises spill over to other non-crisis countries through cross-border bank lending, and the differential transmission to specialized industries. To illustrate this spillover effect, suppose a bank operates in both Poland and Spain while only Poland is experiencing a banking crisis. In order to offset the capital shock in Poland, the bank may reduce lending to Spain in order to rechannel funds to borrowers in Poland through the banks' internal capital market, which gives rise to contagion. How will a bank lending to both Poland and Spain adjust its loan supply in each country? And how does this lending response to a banking crisis in one country depend on industry specialization of banks? We find that banking crises spill over to other non-crisis countries through cross-border lending: Banks operating in a country that experiences a banking crisis reduce loan supply to firms in non-crisis countries by 7 %. Moreover, this spillover effect is strongest to those industries in which the bank is not specialized in. Thus, increasing industry specialization by one standard deviation mutes the spillover effect by 6.5 %, which is almost sufficient to entirely undo the initial contagion. Therefore, industries with lower presence of specialized banks are more prone to cross-border banking crisis contagion.

The main identification challenge in the literature that aims at measuring loan supply effects in cross-country settings is to absorb loan demand. The concern is that changes in firm's demand for loans over time may bias the results on bank lending. Detailed lending data on the international syndicated loan market allows us to address this issue. Following the literature to separate out loan supply from loan demand, we start the analysis on the most granular firm-bank-quarter level where we employ firm-time fixed effects (Khwaja and Mian, 2008; Jiménez, Atif, Peydro and Saurina Salas, 2012; Jiménez, Ongena, Peydró and Saurina, 2014; Morais, Peydro and Ruiz Ortega, 2019). By comparing the lending behavior of specialized banks to unspecialized banks to the same borrower, we address the concern that differences in loan demand biases the results on bank lending. Also, we employ a combination of bank-firm, bank-time and firm-time fixed effects to address a number of alternative explanations. We absorb time-invariant unobservable variables at the bank-firm level, such as distance, through bank-firm fixed effects. Moreover, we absorb unobservable time-varying heterogeneity across banks through bank-time fixed effects, absorbing omitted bank-level variables such as bank size, bank profitability or banks total loan supply. Additionally, we test whether industry specialization is robust to an alternative measure of banks portfolio allocation. In particular, we test whether bank lending by industry specialization can be explained by geographic diversification of banks cross-country lending portfolio, as in Doerr and Schaz (2019). We find that results on industry specialization are robust to banks' geographic diversification, which alleviates concerns on omitted variable bias. Thus, several robustness tests and a comprehensive set of fixed effects show that it is unlikely that the results are driven by individual characteristics of the banks', quality of the firms, or bank-firm specific information that they have collected through previous interactions. Our regressions therefore estimate the marginal propensity of a bank to lend to firms in specialized industries rather to firms in non-specialized industries during a crisis.

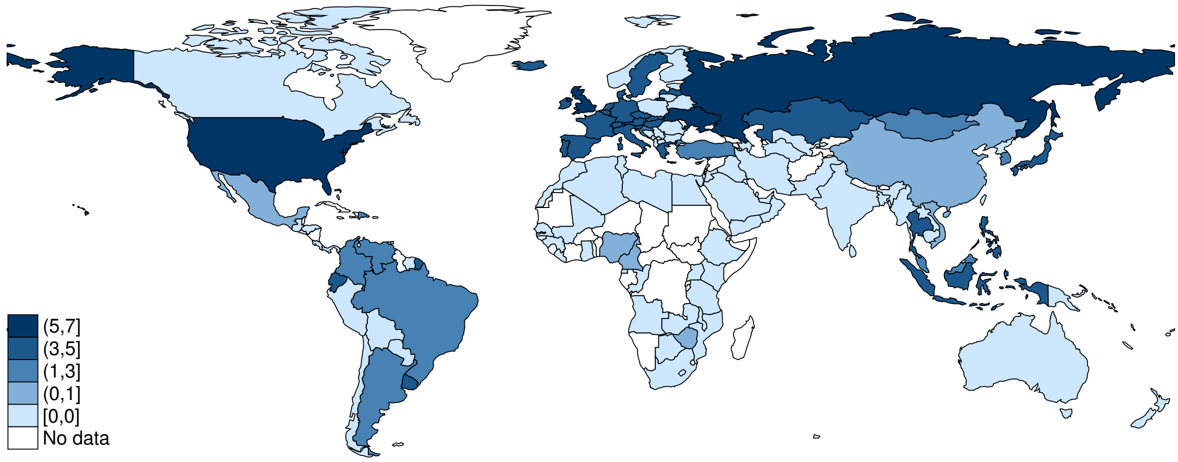
On the bank-industry level, we absorb loan demand through a combination of bank-industry and country-industry-time fixed effects. Here, the identifying assumption is that all firms within a country-industry group change their loan demand similarly during a crisis. In order to test whether firms change their loan demand differentially within industries, we compare this specification with the more demanding firm-time fixed effects at the loan level. While we find that within-industry firm heterogeneity exists, it works against the main finding of our empirical framework and, thus, indicating that the estimation using country-industry-time effects provides lower bounds of coefficients. Taken together, these findings indicate that the positive effect of bank specialization on lending during crisis reflects loan supply.

Our paper contributes to the existing literature in several ways. First, our paper relates to the literature that explores the effects of banks' loan concentration on liquidity provision (Giannetti and Saidi, 2019). In their paper De Jonghe et al. (2016) use Belgium credit register data estimate the effect of banks' sector specialization, together with sector presence and firm risk on banks' lending decisions. In contrast, we use detailed cross-country dataset which allows for assessment of international spillover effects. Moreover, Paravisini et al. (2015) addresses the specialization of lending, but focusing on the export market instead.

Second, our results contribute to the growing literature on bank funding shock transmission and cross-border spillovers, following on methodology developed by Khwaja and Mian (2008). Some authors have focused on the effect of funding shocks on lending (Puri et al., 2011; Cetorelli and Goldberg, 2011), while others adressed cross-border shock transmission from banks' home countries into borrower countries Peek and Rosengren (1997). Instead, we look at the lending response to banking crisis that originate in the borrower country. The importance of geographical specialization has also been adressed in several papers: Giannetti and Laeven (2012) show that the collapse of international markets during financial crises can in part be explained by a flight home effect, while De Haas and Van Horen (2013) show that geographical proximity of banks' connected markets plays a role in banks' portfolio reallocation.

The remainder of the paper is organized as follows. First we provide the description of the data and the construction of variables in Section 2. Next, we discuss the empirical methodology that is used to address the research question, focusing on identification challenges. We present the results of our main analysis in two steps: Lending to firms at the bank-firm level and lending to industries at the bank-industry level (Section 4). In Section 5 we investigate the implications of our findings, by estimating real effects,

FIGURE 1: **Number of Banking Crisis Years by Country**



Note: This figure shows the number of years with a banking crisis for each country. Banking crises are defined in Laeven and Valencia (2013). Darker colors show countries with more banking crisis years, lighter colors those with less.

focusing on industry specific value added and employment. Finally, results on cross-border spillover effects are presented in Section 6.

2 Data

For our main analysis and the construction of bank industry specialization, we use data on worldwide syndicated lending. We additionally use country-industry data and further information on borrowing firms' balance sheets. Loan-level data with detailed bank-firm relations come from Thomson Reuters Dealscan and covers the universe of syndicated loans. Macroeconomic variables come from the World Bank's World Development Indicators. Industry-level data are drawn from EU KLEMS Growth and Productivity Accounts to provide data on productivity and employment for the analysis of real effects.

Data on banking crises are drawn from Laeven and Valencia (2013)'s Systemic Banking Crises Database, which provides country-year-level information on episodes of financial distress.[3] From 1995 to 2012, it reports 189 banking crisis (BC) observations at the bank-year level. The two conditions that define a banking crisis are i) significant signs of financial distress in the banking system (such as bank runs, losses in the banking system,

[3](Laeven and Valencia, 2013) is the most comprehensive database on financial crises occuring after 1970.

and/or bank liquidations); and ii) significant banking policy intervention measures in response to the losses in the banking system. Figure 1 plots the number of years with a banking crisis for each country. In our sample, there is a concentration of financial turmoil around the time of the Asian crisis and from 2008 onward, during the Great Financial Crisis.

To construct main variables, we use Dealscan data on syndicated loans. Syndicated lending constitutes a significant share of total lending. Around one-third of total international lending is done through the syndicated loan market and it is an important source of financing in both developed and emerging economies (Cerutti et al., 2015). Syndicated loans are issued jointly by a group of banks to a single borrower. The lending syndicate includes at least one lead bank (also called lead arranger) and usually further participant banks. Lead banks negotiate terms and conditions of deals, perform due diligence, and organize participants. Therefore, lead arrangers stand in direct contact with the borrower and retain larger loan shares for signaling purposes. Participants are usually not in direct contact with the borrower, but merely supply credit. Compared to other types of bank loans, syndicated loans are on average larger in volume and issued to bigger borrowers.

Dealscan provides extensive information on syndicated loans at origination, including loan amount, maturity, and interest, as well as identity of lenders and borrowers. We restrict our analysis to loans by banks to non-financial firms and consider lending only by commercial, savings, cooperative and investment banks.[4] All data are aggregated at banks' and firms' parent company, consistent with the literature. We keep only lead arrangers and drop participants from our sample as we are interested in loan supply conditional on bank expertise in the specific industry. We expect banks to collect soft information on an industry through repeated interaction with borrowers similar to Boot (2000). As participants are usually not in direct contact with the borrower they are not able to collect soft information on the specific industry upon supplying credit; hence, participants are excluded from the sample.

Our full sample covers the years 1995 to 2010 and is composed of three separate levels of aggregation. First, we construct data to the bank-firm-quarter level, containing information on 37,666 firms and 2,001 banks forming a total of 899,098 observations. Second, we aggregate this data to form 487,098 observations at the bank-industry-quarter level. Third, we aggregte data to the country-industry-year level consisting of 11,852

[4]In Dealscan, we include only the lender types Commercial Banks, Finance Companies, Investment Banks, Mortgage Banks, Thrift/S&L, and Trust Companies. Investment banks constitute 3 % of our sample and excluding them does not change results. Borrower types included are Corporations, Insurance Companies, Law Firms, Leasing Companies and Other. See Doerr and Schaz (2019) and Schaz (2019) for further details on data construction using Dealscan data.

TABLE 1: **Summary Statistics (*bank-firm-level sample*)**

VARIABLES	mean	sd	min	max	N
Industry specialization $\in$ [0,1]	0.03	0.09	0.00	1.00	899,098
Loan volume ($m)	181.91	313.30	0.07	2,000	899,098
Loan growth %	4.02	1.96	-3.08	7.94	899,098
Banking crisis $\in$ {0,1}	0.26	0.44	0.00	1.00	899,098
Connected countries $\in$ {0,1}	0.38	0.48	0.00	1.00	899,098

Note: This table shows summary statistics of variables at the bank-firm-quarter level. *Industry specialization* is the relative importance of an industry for a bank (across all countries), defined as the ratio of all credit granted by bank b to industry i in quarter q relative to bank b's total credit granted in the same period. *Loan volume* (in millions of USD) is the outstanding loan volume by bank b to firm f in quarter q. *Loan growth* is the quarterly growth of *Loan volume*. *Banking crisis (BC)* is a dummy variable with value one during banking crises in the firm country. *Connected countries* is a dummy variable which equals one for all non-crisis countries c' ($\neq c$), to which bank b is actively lending in t.

observations. Tables 1, 2 and 3 provide summary statistics of the main variables for all three levels of data aggregation.

To measure industry specialization of a bank, we construct a variable based on the relative importance of an industry for a bank by lending volume across all countries. We define industry specialization as the ratio of all loans granted by bank b to all borrowers from industry i relative to bank b's total loans granted in quarter t:

$$Industry\ specialization_{b,i,t} = \frac{\sum_{f=1}^{F} loans_{b,f,i,t}}{\sum_{i=1}^{I}\sum_{f=1}^{F} loans_{b,f,i,t}}, \tag{1}$$

where F captures the total number of firms with outstanding loan volume from bank b that belong to industry i at time t. Industries are defined as four-digit Standard Industrial Classification (SIC) codes as reported in Dealscan. Similarly, I is the total number of industries i to which bank b has outstanding loan volume at time t. $Loans_{b,f,i,t}$ measures the total outstanding lending volume (in USD m) from bank b to borrowing firm f from industry i in t. $Industry\ specialization_{b,i,t}$ takes values between 0 and 1, where 0 means absence of lending to industry i, while 1 indicates that all recorded lending by a specific bank goes industry i at time t. We use this variable both for analysis at the bank-firm-quarter and at the bank-industry quarter level. Figure 2 plots the left-skewed distribution of banks' *industry specialization* around the mean value of 0.03 at the bank-firm-quarter level; this distribution shows that banks are highly diversified across industries.

TABLE 2: **Summary Statistics (*bank-industry-level sample*)**

VARIABLES	mean	sd	min	max	N
Industry specialization $\in$ [0,1]	0.04	0.11	0.00	1.00	487,098
Loan volume ($m)	266.98	490.18	0.07	5,810	487,098
Loan growth %	4.36	1.86	-2.70	8.67	487,098
Banking crisis $\in$ {0,1}	0.25	0.43	0.00	1.00	487,098
Connected countries $\in$ {0,1}	0.33	0.47	0.00	1.00	487,098

Note: This table shows summary statistics of variables at the bank-industry-quarter level. *Industry specialization* is the relative importance of an industry for a bank (across all countries), defined as the ratio of all credit granted by bank b to industry i in quarter q relative to bank b's total credit granted in the same period. *Loan volume* (in millions of USD) is the outstanding loan volume by bank b to all borrowers of industry i in quarter q. *Loan growth* is the quarterly growth of *Loan volume. Banking crisis (BC)* is a dummy variable with value one during banking crises in the borrower country. *Connected countries* is a dummy variable which equals one for all non-crisis countries c' ($\neq c$), to which bank b is actively lending in t.

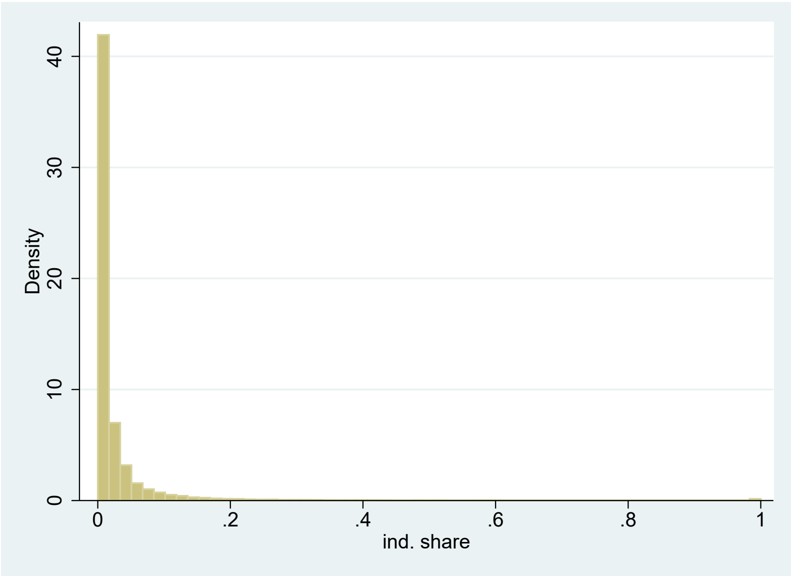
TABLE 3: **Summary Statistics (*country-industry-level sample*)**

VARIABLES	mean	sd	min	max	N
Loan volume ($m)	4,003.10	17,853.30	0.02	309,260.91	11,852
Loan growth %	5.67	2.02	-0.69	11.41	11,416
Exposure $\in$ [0,1]	0.06	0.11	0.00	1.00	11,852
Value added ($m)	87,824.52	214,611.06	0.00	2,080,330	4,773
Number of employees (m)	635.00	1,479.71	1.66	15,828	4,162
Value added growth %	9.93	1.70	5.29	14.33	4,693
Number of emplyees growth %	5.24	1.51	0.69	9.14	4,093
Banking crisis $\in$ {0,1}	0.16	0.37	0.00	1.00	11,852

Note: This table shows summary statistics of variables at country-industry-year level. *Loan volume* (in millions of USD) is loan obtained by industry i in year y. *Loan growth* is the annual growth of *Loan volume*. *Exposure* is exposure of an industry i to specialized banks in year y. *Value added* (in millions of $) is country-industry specific value added. *Number of employees* (in millions) is country-industry specific number of employees. *Value added growth* is annual growth of country-industry specific *Value added. Number of employees growth* is annual growth of country-industry specific number of *Number of employees. Banking crisis (BC)* is a dummy with value one during banking crises in the borrower country.

For the analysis of real effects we construct data varying at the country-industry-quarter level for which Table 3 shows summary statistics. For this purpose, we match aggregate bank lending with data on employment and value added at the industry level for 31 countries covering around 85 % of our observations in the loan level sample. We

Figure 2: **Distribution of Banks' Industry Specialization**



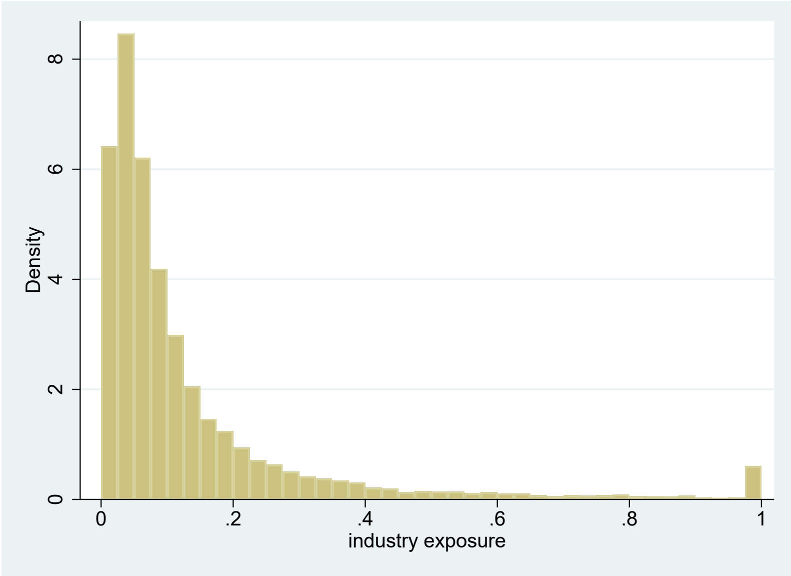
Note: This figure shows the histogram of banks' industry specialization at the bank-firm-quarter level, measured as the ratio of loans granted by bank b to all borrowers of industry i in time period t relative to bank b's total lending granted in the same period.

construct the variable $Exposure_{c,i,t}$ capturing the exposure of industry i in country c to banks specialized to this industry in quarter t. That is, exposure captures the reliance on lending from banks that are specialized in the respective industry. In particular, we weigh the outstanding loan volume from bank b to all borrowers from industry i in country c with the respective industry specialization value ($Industry\ specialization_{b,i,y}$) of bank b in year y. Then, we divide this weighted loan volume by the total outstanding loan volume to all borrowers in industry i from country c:

$$Exposure_{c,i,y} = \frac{\sum_{b=1}^{B} Industry\ specialization_{b,i,y} \cdot loan_{b,c,i,y}}{\sum_{b=1}^{B} loan_{b,c,i,y}}, \tag{2}$$

where B is the total number of banks with outstanding loans to firms in industry i from country c at year y. $Industry\ specialization_{b,i,y}$ is defined as above in Equation (1) and then annualized; $loan_{b,c,i,y}$ measures the total outstanding lending volume (in USD m) from bank b to all borrowers in industry i from country c at year y. $Exposure_{c,i,y}$ takes values between 0 and 1, where $Exposure = 0$ means that firms from this industry borrow entirely from banks that do not specialize in this industry ($Industry\ specialization = 0\ \forall\ B$). Higher values of exposure indicates stronger lending

Figure 3: **Distribution of Industries' Exposure to Specialized Banks**



Note: This figure shows the histogram of industries' exposure to specialized bank at the country-industry-year level. Exposure is measured as the ratio of all credit obtained by industry i from specialized banks in time period t relative to industry i's credit obtained from all banks in the same period.

from banks that are specialized to the respective industry. Figure 3 plots the distribution of exposure across the sample. Most industries are lending from banks that are not very much specialized in the respective industry, as the left-skewed distribution of exposure around mean 0.06 suggests.

3 Empirical Methodology

We examine how banks' industry specialization affects lending during banking crises in four steps at three levels of aggregation. First, we isolate loan supply from loan demand on the granular firm-bank-quarter level (loan level) to establish lending to firms. Second, we analyze bank lending behavior to specialized industries on aggregate at bank-industry-quarter level. Third, we further aggregate the data to the country-industry-year level, in order to establish real effects effects on industry-level employment and value added. Finally, we analyze whether banking crises spill over to other non-crisis countries through cross-border lending and whether this contagion depends on banks' industry specialization.

3.1 Lending to Firms

Our baseline specification tests how bank industry specialization affects loan volume for each firm-bank pair. To assess the effect of specialization on loan supply during banking crises in the borrower country, we interact industry specialization with a banking crisis dummy:

$$log(loan)_{b,f,t} = \beta_1 BC_{c,t} + \beta_2 SPEC_{b,i,t-1} + \beta_3 SPEC_{b,i,t-1} \times BC_{c,t} + \phi_{b,f} + \theta_{b,t} + \tau_{f,t} + \varepsilon_{b,f,t} \tag{3}$$

The dependent variable is log of total outstanding loan volume by bank b to firm f in quarter t; *banking crisis (BC)* is a dummy with value one during banking crises in the firm country c in quarter t. $SPEC_{b,i,t-1}$ is defined as bank industry specialization as defined in Equation (1). In order to avoid contemporaneous effects of the banking crisis on industry specialization, we lag *SPEC* by one period. $\phi_{b,f}$ denote bank-firm fixed effects, $\theta_{b,t}$ bank-time fixed effects and $\tau_{f,t}$ firm-time fixed effects. We cluster standard errors on the bank level to account for correlation of firm lending relationships to the same bank. The coefficients of interest is β_3 captures loan supply to firms in specialized industries compared to firms in non-specialized industries of the bank during crises. The identifying assumption is that banking crises at the aggregate country level are exogenous to the granular bank-firm lending decision. Banking crises are times of aggregate scarce capital and thus β_3 captures how this funding shock is transmitted to firms depending on banks' industry specialization.

The key identification challenge is to isolate loan supply by absorbing changes in loan demand. It may well be that banks specialize in certain industries because firms in this industry are more profitable or crisis resilient. Thus, loan demand by firms in specialized industries may be higher during banking crises, which affects banks lending decision. Due to the granularity of our data, we are able to address this challenge. First, firm-bank fixed effects use the variation within the same firm-bank relationship over time and thereby control for unobservable and time-invariant bank and firm heterogeneity (such as location or legal form); firm-bank fixed effects also control for unobservable time-invariant characteristics at the bank-firm level, such as distance and relationship. Second, firm-time fixed effects allow shocks to affect each firm differentially at each point in time. Doing so, we control for unobservable time-varying firm characteristics (for example firm profit, risk and managerial quality) to identify loan supply.[5] Third, bank-time fixed effects capture all time-varying unobserved heterogeneity at the bank level, controlling for idiosyncratic shocks to banks' total credit supply and other changes at the bank-time level.

Essentially, we measure the marginal propensity of bank b to lend to firm f that is part of their specialized industry i rather than to other firms from non-specialized industries during a crisis. After absorbing any changes in loan demand our estimates reflect loan supply effects according to the literature that followed Khwaja and Mian (2008).[6]

3.2 Lending to Industries

While the previous section identifies loan supply for each bank-firm connection, it is not clear whether banks shield their specialized industries on aggregate during a crisis. Instead, banks may keep lending to specific firms within a specialized industry as they know this industry particularly well. To analyze whether banks actually protect their specialized industries on aggregate, rather than cherry-picking firms within a specialized industry they know best, we now move to the coarser bank-industry-quarter level estimating following regression equation:

$$\Delta\ loan_{b,i,t} = \gamma_1 BC_{c,t} + \gamma_2 SPEC_{b,i,t-1} + \gamma_3 SPEC_{b,i,t-1} \times BC_{c,t} + \theta_{b,i} + \tau_{c,i,t} + \psi_{b,t} + \varepsilon_{b,i,t} \tag{4}$$

The dependent variable $\Delta\ loan_{b,i,t}$ denotes the log difference of outstanding syndicated loan volume of *all* firms in industry i borrowing from bank b at quarter t. As before, the banking crisis dummy $BC_{c,t}$ takes value one during a crisis in firm country c in quarter t; $SPEC_{b,i,t-1}$ denotes bank b's industry specialization in industry i at time t as defined in Equation (1). We lag *SPEC* by one period in order to avoid contemporaneous effects of the banking crisis on industry specialization. We cluster standard errors on the bank level to account for correlation of firm lending relationships to the same bank across industries.

[5] For each firm-year pair, firm-time fixed effects require observations from at least two banks. On the syndicated loan market, around 97 % of all loans satisfy this condition. The sample selection effect due to this demanding specification is therefore negligible.

[6] Further studies identfying loan supply effects using firm-time fixed effects are Jiménez, Ongena, Peydró and Saurina (2014) and Morais, Peydro and Ruiz Ortega (2019).

Similar to the loan level, the key identification challenge is to absorb loan demand in order to interpret results as loan supply. To do so, we estimate variants of regression Equation (4) employing different combinations of fixed effects. $\theta_{b,i}$ denote bank and industry fixed effects to absorb time-invariant characteristics at the bank-industry level. $\tau_{c,i,t}$ capture country-industry-time fixed effects in order to absorb time-varying heterogeneity, such as loan demand, at the industry level. $\psi_{b,t}$ are bank-time fixed effects and capture all time-varying unobserved heterogeneity across banks. For instance, $\psi_{b,t}$ control for idiosyncratic shocks to banks' total credit supply and other changes at the bank-time level. The main coefficient of interest, γ_3, captures the differential propensity of bank b to lend to borrowers in their specialized industry i rather than to borrowers from non-specialized industries during a crisis.

3.3 Real Effects

We investigate whether lending to firms in specialized industries compared to firms in non-specialized industries during crises has real effects for the economy at the industry level. The previous steps test whether banks prioritize firms within (bank-firm level) and the specialized industry itself (bank-industry level). However, firms in industries that receive less credit during a crisis may able to substitute this fall in lending by switching banks or resorting to alternative forms of funding. Perfect credit substitution would, hence, lead to a mere recomposition of firms' funding side, leaving their effective financial position untouched. To test for real effects at the industry level, we move the analysis to the country-industry-year level to match aggregate bank lending with data on employment and value added at the industry level by country. In order to examine whether lending to specialized industries leads to real effects to the respective industries, we estimate following regression:

$$\begin{aligned} log(employment)_{c,i,y} = {} & \delta_1 BC_{c,y} + \delta_2 Exposure_{c,i,y-1} \\ & + \delta_3 BC_{c,y} \times Exposure_{c,i,y-1} + \phi_{c,i} + \theta_{c,y} + \varepsilon_{c,i,y} \end{aligned} \tag{5}$$

The dependent variable is the log of employment (in million) of industry i in country c at year y. In variants of the specification, we replace the dependent variable by the log of value added (in million USD) of industry i in country c at year y. $Exposure_{c,i,y-1}$ captures the reliance of industry i in country c on lending from banks that are specialized in the respective industry as defined in Equation (2). We lag *Exposure* by one year in order to avoid contemporaneous effects of the banking crisis on this metric. To account for heterogeneities both across industries and across countries, we exploit the within-country and within-industry variation by adding industry, country and country-industry fixed effects respectively (denoted by $\phi_{c,i}$). Additionally, we address time-varying demand shocks, for example through heterogeneous business cycle developments, by adding country-year fixed effects (denoted by $\theta_{c,y}$). The coefficient of interest is on the interaction term ($BC \times Exposure$) capturing the differential effect of banking crises on employment, comparing industries with high reliance on specialized banks with those industries that borrow instead more from unspecialized banks.

3.4 Spillover Effects

We now turn to the question how banking crises spillover to other countries through cross-border bank lending and whether industry specialization mutes or amplifies this effect. We define a spillover effect of a banking crisis country to a third country through the reduction in lending of a bank that operates in both countries. Suppose a bank operates both in Poland and Spain and only Poland experiences a banking crisis. To offset the shock to capital in Poland, the bank may reduce lending to borrowers in Spain in order to rechannel funds towards Poland, through the banks' internal capital market, in order to maintain lending. Therefore, banking crises may spill over to countries that are themselves unaffected by a banking crisis via a connection to a banking crisis country through a bank that operates in both markets.

To measure spillover effects we introduce the dummy variable $connected_{b,c',t}$, which equals one for all non-crisis countries c' ($\neq c$), to which bank b is actively lending in t, iff at least one other country c, to which bank b is actively lending, experiences a banking crisis in t. In the spirit of Giroud and Mueller (2015, 2017) the coefficient on *connected* shows how lending changes to all *connected countries* c' that borrow from bank b, but do not experience a crisis themselves. To test for spillover effects we run variants of following regression equation at the bank-firm-quarter level:

$$\begin{aligned} \text{Log(Loan)}_{b,f,t} = \rho_1\ BC_{c,t} + \rho_2\ SPEC_{b,i,t-1} + \rho_3\ connected_{b,c',t} + \rho_4\ SPEC_{b,i,t-1} \times BC_{c,t} + \\ + \rho_5\ connected_{b,c',t} \times SPEC_{b,i,t-1} + \phi_{b,f} + \theta_{b,t} + \tau_{f,t} + \varepsilon_{f,b,t} \end{aligned} \tag{6}$$

where the dependent variable is the log outstanding loan volume of bank b to firm f at quarter t as in Equation (3). Following the most demanding specification presented in the last column of Table 4, we use bank-firm fixed effects to exploit the within-bank-firm variation in the estimation; bank-time fixed effects are used to absorb bank-level loan supply and other time-varying unobservable such as bank b's size or profitability; to absorb loan demand, we employ country-industry-time or bank-time fixed effects. The dummy variable $connected_{b,c',t}$, which equals one for all non-crisis countries $c' \neq c$ in which bank b is actively lending to and that do not experience a contemporaneous banking crisis ($BC_{c',t} \neq 1$), if at least one other active lending country c of bank b experiences a banking crisis at time t ($BC_{c,t} = 1$). To analyze the differential impact of bank specialization on crisis spillover effects, we interact *connected* with bank's industry *specialization*. The coefficient of interest, ρ_5, measures the differential transmission of lending cuts to specialized industries compared to non-specialized industries in connected countries without crisis.

4 Main Results

We present the main results in two steps. First, we analyze the loan supply effect of bank's industry specialization during banking crises on firms at the bank-firm-year (loan) level. This allows us to control for unobservable time-varying heterogeneities at the bank-level and at the firm-level to absorb loan demand. Second, we analyze effects of industry specialization on banks' overall industry lending at the bank-industry-quarter level.

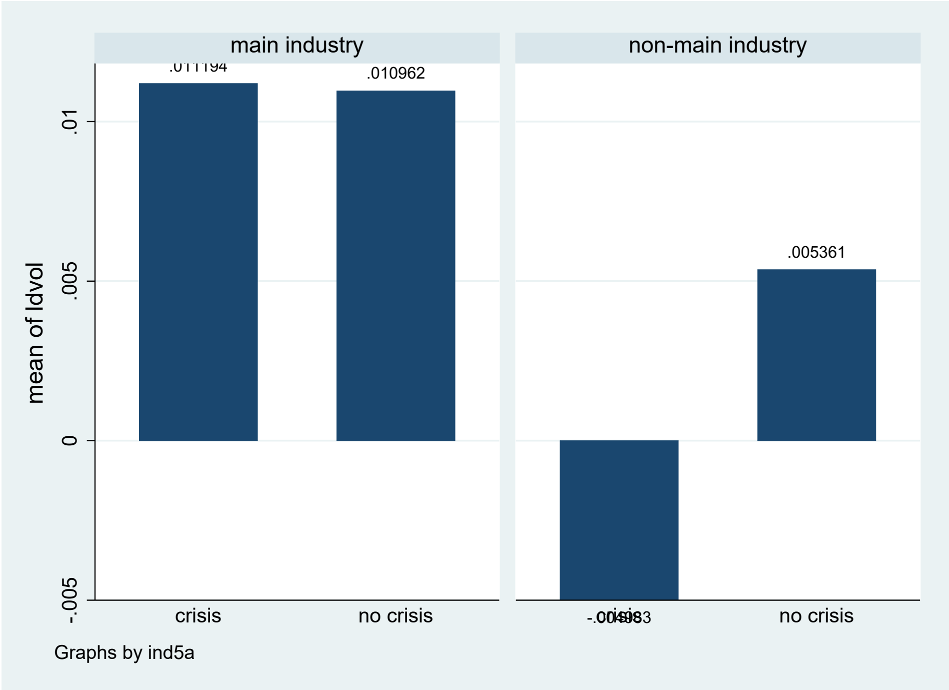
Before we move to the regression analysis, Figure 4 shows the stabilizing effect of bank industry specialization on lending to their main industries during banking crises using simple sample correlations. The figure plots average loan growth during crisis and non-crisis times to all borrowers, comparing this effect to banks' main industries and to their non-main industries. We define main industries as those industries that make up for more than 5 % of the lending share in a bank's loan portfolio as defined in Equation (1).[7] The figure suggests that banks extend more loans to their main industries both in times of crisis and no crisis. Furthermore, the right panel shows that banks reduce lending to borrowers from their non-main industries during banking crises. However, banks maintain lending to firms from their main industry that is similar during crisis and no crisis times. We now show that this pattern holds in regression analysis.

4.1 Lending to Firms

Table 4 presents results for regression Equation (3) at the bank-firm-quarter (loan) level and shows that banks maintain higher loan growth to firms in their specialized industries

[7] As can be seen from Table 1, the mean of banks industry specialization is 0.03 % and using cut-offs between 3 % and 10 % yields similar graphs.

FIGURE 4: **Lending by Industry Specialization in Crisis vs. No-Crisis Times**



Note: This figure shows the difference in loan volume extended to main industries versus non-main industries at the bank-firm-quarter level; comparing banking crisis versus no banking crisis times. Main industries are defined as industries that make up for more than 5 % of the lending share in a bank's loan portfolio as defined in Equation (1).

relative to firms in less represented industries in their loan portfolio. The dependent variable is the log outstanding loan volume of bank b to firm f at quarter t. Column (1) looks at variation within each bank-firm connection through firm-bank fixed effects. Moreover, bank-time fixed effects absorb unobservable heterogeneity at the bank-level in all specifications. Thereby, we measure the marginal propensity of bank b to lend to firm f that is part of their specialized industry i rather than to other firms, which are part of non-specialized industries. The positive and statistically significant main coefficient of *industry specialization* implies that the lending volume to firms within their specialized industries is larger than for firms in unspecialized industries. The coefficient of interest on the interaction term $(SPEC_{b,i,t} * BC_{c,t})$ is statistically significant and positive. During banking crises, increasing industry specialization by one standard deviation increases loan volume to firms by $(0.09 \times 0.4 =)$ 3.6 %.

In order to absorb loan demand, column (2) adds country-industry-time fixed effects

TABLE 4: **Effect of Bank Specialization on Loan Supply to Firms**

VARIABLES	(1) log(loan)	(2) log(loan)	(3) log(loan)
BC × Industry spec.	0.40***	0.23*	0.70**
	(0.14)	(0.13)	(0.31)
Banking crisis (BC)	-0.02		
	(0.02)		
Industry spec.	1.84***	1.92***	2.74***
	(0.17)	(0.17)	(0.32)
Observations	796,033	712,751	270,328
R-squared	0.95	0.96	0.97
Bank*Firm FE	Yes	Yes	Yes
Bank*Time FE	Yes	Yes	Yes
Country*Industry*Time FE	-	Yes	-
Firm*Time FE	-	-	Yes
Clustered SE	Bank	Bank	Bank

Note: This table shows regressions on the bank-firm-quarter (loan) level for different levels of cluster-robust standard errors. The dependent variable is log of total outstanding loan volume by bank b to firm f in quarter t; *Banking crisis (BC)* is a dummy with value one during banking crises in the firm country, as defined in (Laeven2013); *Industry specialization* is measured as the ratio of loans granted by bank b to all borrowers of industry i in time period t relative to bank b's total lending granted in the same period, lagged by one period (quarter). *** $p<0.01$, ** $p<0.05$, * $p<0.1$

to the specification. The coefficient remains positive and statistically significant. To ensure that the positive effect is due to marginal loan supply effect to the firm, column (3) adds more demanding firm-time fixed effects holding the same borrower constant at time t. The positive effect of lending to firms within the specialized industry compared to firms outside that industry increases to ($0.09 \times 0.7 =$) 6.3 % during banking crises. Comparing column (1) with column (3) the coefficient increases after absorbing loan demand, indicating that loan demand by firms in specialized industries is on average weaker and less resilient during crises compared to firms from non-main industries.

The tendency of banks to protect their main industries during crises does not depend on unobservable bank-level heterogeneity as we include bank-time fixed effects. Therefore, any time-varying unobservable variable such as bank b's average loan supply, profitability or size will be absorbed. This identification, thus, captures the marginal propensity of bank b to lend to firm f that lies in a specialized industry rather than to a firm that is part of a non-specialized industry.

Do banks stabilize lending by increasing lending to firms belonging to specialized industries or rather by decreasing lending to firms in non-specialized industries, when capital is scarce during a crisis? To answer this question, we now repeat the estimation

Table 5: **Transmission of Banking Crisis to Main vs. Non-main Industries**

VARIABLES	(1) log(loan)	(2) log(loan)	(3) log(loan)
BC X Top ind. spec.	-0.02	-0.01	0.05***
	(0.01)	(0.01)	(0.02)
BC X Low ind. spec.	-0.08***	-0.08***	-0.07***
	(0.01)	(0.01)	(0.02)
Banking crisis (BC)	0.01		
	(0.02)		
Top ind. spec.	0.21***	0.19***	0.23***
	(0.01)	(0.01)	(0.02)
Low ind. spec.	-0.17***	-0.14***	-0.18***
	(0.02)	(0.02)	(0.02)
Observations	896,740	811,240	348,496
R-squared	0.95	0.96	0.96
Bank*Firm FE	Yes	Yes	Yes
Bank*Time FE	Yes	Yes	Yes
Country*Industry*Time	-	Yes	-
Firm*Time FE	-	-	Yes
Clustered SE	Bank	Bank	Bank

Note: This table shows different effects of lending to firms in main vs. non-main industries on the bank-firm-quarter (loan) level. The dependent variable is the log of total outstanding loan volume by bank b to firm f in quarter t; Main (Top) industry is defined as all firms within bank b's top tercile of industry specialization as defined in Equation (3), lagged by one period. Non-Main (Bottom) industry is defined as all firms within bank b's bottom tercile of industry specialization as defined in Equation (3), lagged by one period. *Banking crisis (BC)* is a dummy with value one during banking crises in the borrower country. *** p<0.01, ** p<0.05, * p<0.1

of regression Equation (3) while replacing industry specialization by a dummy for firms belonging to either their top or bottom terciles of their specialized industries. Column (1) of Table 5 shows that banks reduce lending to firms within their least specialized industries by -8 % compared to firms in the middle tercile, during crises. However, they do not significantly change their lending to firms belonging to their most important industries during a banking crisis. However, this effect turns significant to 5 % higher loan volume for firms in their top tercile of industry specialization, once we absorb loan demand through firm-time fixed effects in column (3). Therefore, these results suggest that banks reduce lending most to firms part of their least specialized industries; Firms in their most specialized industries receive, if anything, more lending than firms in their

TABLE 6: **Effect of Bank Specialization on Lending to Industries**

VARIABLES	(1) Δ loan	(2) Δ loan	(3) Δ loan	(4) Δ loan
Banking crisis (BC)	-0.01***	-0.02***		
	(0.00)	(0.00)		
Industry spec.	0.05***	0.15***	0.16***	0.34***
	(0.01)	(0.01)	(0.01)	(0.03)
BC × Industry spec.	0.02***	0.04***	0.02**	0.03
	(0.01)	(0.01)	(0.01)	(0.02)
Observations	422,076	421,213	413,162	412,010
R-squared	0.00	0.02	0.20	0.23
Bank FE	Yes	-	-	-
Industry FE	Yes	-	-	-
Bank*Industry FE	-	Yes	Yes	Yes
Country*Industry*Time FE	-	-	Yes	Yes
Bank*Time FE	-	-	-	Yes
Clustered SE	Bank	Bank	Bank	Bank

Note: This table shows regressions on the bank-industry-quarter level. The dependent variable is log difference of total outstanding loan volume by bank b to all borrowers in industry i in quarter t; *banking crisis (BC)* is a dummy with value one during banking crises in the firm country; *Industry specialization* is measured as the ratio of loans granted by bank b to all borrowers of industry i in time period t relative to bank b's total lending granted in the same period, lagged by one period (quarter). *** p<0.01, ** p<0.05, * p<0.1

middle tercile during a banking crisis.

To sum up, several robustness tests through a comprehensive set of fixed effects provide evidence that it is unlikely that the results are driven by individual characteristics of the banks', quality of the firms, or bank-firm specific information that they have collected through previous interactions. Therefore, this suggests that banks shield main-industry firms from the negative loan supply shock of the banking crisis.

4.2 Lending to Industries

To analyze whether banks actually protect their specialized industries on aggregate, rather than cherry-picking firms within a specialized industry they know best, we now move to the coarser bank-industry-quarter level. While the previous section identifies loan supply for each bank-firm connection, it is not clear whether banks shield their specialized industries on aggregate during a crisis. Instead, banks may keep lending to specific firms within a specialized industry as they know this industry particularly well.

Table 6 presents results for regression Equation (4) at the bank-industry-quarter level highlighting that banks protect their main industries during crises. The dependent variable is the log difference of bank b's total lending to industry i at quarter t. For estimation, column (1) uses the within-bank and within-industry variation through bank and industry fixed effects respectively; Column (2) uses the within-bank-firm variation and thus absorbs variables at the bank-firm level, such as distance. Banks' loan growth to specialized industries is higher than to non-specialized industries in normal times, as indicated by the positive coefficient on industry specialization. During a banking crisis, banks reduce loan growth to all industries by -2 % on average. However, banks increase overall lending to their specialized industries during a banking crisis. Inreasing industry specialization by one standard deviation increases loan volume to industry i by $(0.11 \times 0.04 =)$ 0.4 %, during banking crises.

In order to rule out that the effects are not driven by loan demand by heterogeneous developments of industries across countries, we add country-industry-time fixed effects in column (3). Due to the aggregation from the bank-firm to the bank-industry level, the inclusion of bank-time fixed effects is not possible any longer, which reduces the strength of the loan supply identification. The identifying assumption is now that firms within each country-industry group change their loan demand similarly during a banking crisis. After including country-industry-time fixed effects, the coefficient of interest remains positive and statistically significant. Taken together with results at the bank-firm-time level in Table 4 it is, thus, unlikely that banks' lending prioritization of their main industry is driven by loan demand. In column (4), we control for time-varying heterogeneity at the bank-level by adding bank-time fixed effects to the regression. The coefficient of interest on the interaction ($SPEC \times BC$) now remains positive at similar magnitude as in the previous specifications, but becomes statistically insignificant. This implies that either the power of the test decreases due to the high amount of variation reduced through the three layers of fixed effects at this coarse level of aggregation, or, that bank-level heterogeneity explains the coefficient. However, since the coefficient rises from column (3) to column (4) in magnitude and, importantly, remains positive, we believe that the insignificance is due to the reduction in the power of the test.

Overall, the results at both the bank-firm and bank-industry level suggest that banks protect their main industries during crises. Banks shield both firms within and the specialized industry itself from the negative loan supply ensuing due to the banking crisis. Thus, banks transmit the banking crisis by reducing lending to firms that belong to those industries in which the bank is not specialized in.

Table 7: **Impact of Bank Specialization on Industry Employment**

VARIABLES	(1) Log(empl.)	(2) Log(empl.)	(3) Log(empl.)	(4) Log(empl.)
BC X Industry exp.	1.30***	1.27***	0.42***	0.25***
	(0.41)	(0.41)	(0.05)	(0.06)
Banking crisis (BC)	-0.17***	-0.10	-0.05***	
	(0.05)	(0.08)	(0.01)	
Industry exposure	0.86***	0.85***	-0.00	0.02
	(0.14)	(0.14)	(0.02)	(0.02)
Observations	3,856	3,856	3,847	3,831
R-squared	0.56	0.56	0.99	1.00
Country FE	Yes	Yes	-	-
Year FE	-	Yes	Yes	-
Country*Industry FE	-	-	Yes	Yes
Country*Year FE	-	-	-	Yes

Note: This table shows regressions on the country-industry-year (country) level. The dependent variable is the log employment of industry i in year y; *banking crisis (BC)* is a dummy with value one during banking crises in the firm country. *Industry exposure* is the reliance of an industry i in lending from banks specialized in the respective industry as defined in Equation (2), and is lagged by one period. *** p<0.01, ** p<0.05, * p<0.1

5 Real Effects

We now analyze whether the positive loan supply effect to firms in specialized industries compared to firms in non-specialized industries during crises has real effects for the economy at the industry-level. In the analysis presented in Section 4, we provided evidence that banks prioritize both firms (bank-firm-level) within and the specialized industry itself (bank-industry-level). Yet, firms in unspecialized industries may be able to switch banks or resort to alternative forms of funding in order to mitigate the fall in credit access. This credit substitution would lead to a mere recomposition of firms' liability side and, hence, undo the initial negative loan supply effect to firms in non-specialized industries. In order to establish a link between lending to specialized industries and real effects, we now move to the country-industry-year level. We find that industries with higher exposure to specialized industries have more stable economic outcomes, both in terms of employment and productivity, than industries with less exposure during crises.

Table 7 shows results for the estimation of regression Equation (5) at the country-industry-year level. The dependent variable is the log of employment (in million) of industry i in country c at year y. Column (1) uses the within-country variation through country fixed effects. Industry wide employment is 17 % lower during banking crises than in normal times, as the negative coefficient on *banking crisis* indicates. The coefficient of interest on the interaction term ($BC \times Industry\ Exposure$) is positive and statistically significant across specifications. During banking crises, increasing industry exposure to specialized banks by one standard deviation increases employment in industry i by $(0.11 \times 1.30 =)$ 14.3 %. However, effects may be driven by factors specific to a particular year; so we add year fixed effects in column (2) to use only the within-year variation. As results may be driven by heterogeneities both across industries and differently so across countries, we then add country-industry fixed effects in column (3), to use the within variation of an industry in a particular country over time. During banking crises, industry wide employment is now 5 % lower than during normal times. Increasing industry exposure to specialized banks by one standard deviation increases employment in industry i by $(0.11 \times 0.42 =)$ 4.6 % during banking crises.

To remove time-varying demand shocks as some country may experience more stable economic development during crises than others, we then add country-year fixed effects in column (4). This removes time-varying differences in economic development consumption and loan demand that may drive employment due to business-cycle movements. We find that the coefficient of interest becomes smaller but remains positive and statistically significant. The effect remains economically significant as increasing industry exposure by one standard deviation increases employment by $(0.11 \times 0.25 =)$ 2.8 % during banking crises. Comparing columns (3) and (4), we find evidence that absorbing economic development and loan demand reduces the coefficient of interest by 40 %. This suggests that controlling for demand factors is important and not doing so may overestimate the effect, but that the story cannot be fully explained by heterogeneous economic development only. After controlling for loan demand, industries with higher exposure to specialized banks experience more stable development in employment than industries with lower exposure to specialized banks during crises.

In Table 8, we look at an additional real economic outcome by repeating the previous regression for value added. The dependent variable is now the log of value added (in million USD) of industry i in country c at year y. We repeat the same specifications used in Table 7 and find that the coefficient of interest remains at similar magnitude and statistical significance. In column (4), which is the specification that uses the within-country-industry variation and absorbs business cycle factors at the country-year level we find that stronger exposure to specialized banks increases industry-wide value added during crises. Increasing industry exposure to specialized banks by one standard deviation increases value added in industry i by $(0.11 \times 0.15 =)$ 1.7 % during banking crises.

Overall, we provide evidence that a stronger exposure to industries with specialized industries during crises, has real effects for the economy at the industry-level. Industries that are borrowing more from banks that are specialized in this particular industry, experience a more stable economic development, both in terms of employment and value

TABLE 8: **Impact of Bank Specialization on Industry Value Added**

VARIABLES	(1) Log(VA)	(2) Log(VA)	(3) Log(VA)	(4) Log(VA)
BC X Industry exp.	1.25***	1.40***	0.22***	0.15**
	(0.36)	(0.35)	(0.07)	(0.07)
Banking crisis (BC)	0.01	-0.20***	-0.10***	
	(0.05)	(0.07)	(0.01)	
Industry exposure	0.59***	0.77***	0.00	0.02
	(0.12)	(0.12)	(0.03)	(0.03)
Observations	4,353	4,353	4,347	4,323
R-squared	0.70	0.71	0.99	0.99
Country FE	Yes	Yes	-	-
Year FE	-	Yes	Yes	-
Country*Industry FE	-	-	Yes	Yes
Country*Year FE	-	-	-	Yes

Note: This table shows regressions on the country-industry-year (country) level. The dependent variable is log of value added of industry i in year y; *banking crisis (BC)* is a dummy with value one during banking crises in the firm country; *Industry exposure* is the reliance of an industry i in lending from banks specialized in the respective industry as defined in Equation (2), and is lagged by one period. *** p<0.01, ** p<0.05, * p<0.1

added, which cushions the negative real effects of the banking crisis on this industry.

6 Spillover Effects

We now turn to the question how banking crises spillover to other non-crisis countries through cross-border lending and the differential impact of industry specialization on this spillover effect. We define a spillover effect of a banking crisis country to a non-crisis country through the reduction in lending of a bank that operates in both countries. To offset the negative capital shock in the crisis country, a bank may reduce lending from a non-crisis in order to rechannel funds within the internal bank capital market to the crisis country, giving rise to contagion.[8] We document evidence on spillover effects from crisis to non-crisis countries through cross-border lending. Moreover, we find that banks shield firms that belong to their specialized industries from this spillover effect.

Table 9 shows results of estimating regression Equation (6) at the bank-firm-quarter level. The dependent variable is log outstanding loan volume of bank b to firm f at

[8]To illustrate the spillover effect, suppose a bank operates both in Poland and Spain where only Poland is experiencing a banking crisis. To offset the capital shock in Poland, the bank may reduce lending to Spain in order to rechannel funds towards Poland, through the banks' internal capital market, in order to maintain lending.

TABLE 9: **Spillover Effects to Firms by Bank Specialization**

VARIABLES	(1) log(loan)	(2) log(loan)	(3) log(loan)	(4) log(loan)
CON × Industry spec.		1.63***	0.72***	1.50***
		(0.23)	(0.22)	(0.28)
BC × Industry spec.			0.64***	1.42***
			(0.15)	(0.31)
Industry spec.			2.64***	4.35***
			(0.18)	(0.32)
Connected countries	0.00	-0.07*	-0.03	-0.03
	(0.03)	(0.04)	(0.03)	(0.06)
Observations	811,240	811,240	811,240	348,496
R-squared	0.96	0.96	0.96	0.96
Bank*Firm FE	Yes	Yes	Yes	Yes
Bank*Time FE	Yes	Yes	Yes	Yes
Country*Industry*Time FE	Yes	Yes	Yes	-
Firm*Time FE	-	-	-	Yes
Clustered SE	Bank	Bank	Bank	Bank

Note: This table shows spillover effects on the bank-firm-quarter (loan) level for different levels of cluster-robust standard errors. The dependent variable is log of total outstanding loan volume by bank b to firm f in quarter t; *Banking crisis (BC)* is a dummy with value one during banking crises in the firm country, as defined in (Laeven2013); *Industry specialization* is measured as the ratio of loans granted by bank b to all borrowers of industry i in time period t relative to bank b's total lending granted in the same period, lagged by one period (quarter). *Connected countries* is a dummy variable which equals one for all non-crisis countries c' ($\neq c$), to which bank b is actively lending in t. *** p<0.01, ** p<0.05, * p<0.1

quarter t. In columns $(1) - (3)$ we employ bank-firm fixed effects to use the within-bank-firm variation in the estimation. Moreover, we add bank-time fixed effects are used to absorb time-varying unobservable factors at the bank level such as the bank's total loan supply, profitability or size. In order to absorb loan demand, we implement firm-time fixed effects similar to column (2) in Table 4 similar to Khwaja and Mian (2008). In column (2), we find evidence for spillover effects as banks that operate in a country that experience a banking crisis reduce loan supply to firms in connected non-crisis countries by 7 %. The coefficient of interest on the interaction term ($connected \times SPEC$) is positive and statistically significant. Increasing industry specialization by one standard deviation increases loan volume to firms by $(0.09 \times 1.63) = 14.7$ % and therefore mitigates spillover effects to the connected country. After horse-racing this coefficient with the interaction effect between *banking crisis* and *industry specialization* in column (3), this effect reduces by half to $(0.09 \times 0.72) = 6.5$ %. Results are robust to the absorption of loan demand through firm-time fixed effects as reported in column (4).

Next, we examine whether banking crises spill over to entire industries and whether banks transmit such a contagion differentially to their specialized industries. Table 10 reports results of estimating the regression at the bank-industry-quarter level. The dependent variable is the log difference of bank b's total lending to industry i at quarter t. Column (2) shows that banks reduce loan growth to all industries that are in a borrower country that experiences a banking crisis by 2 %. Additionally, we find evidence for contagion effects as banks reduce lending to industries that are in *connected* non-crisis countries by 1 %. This suggests that banking crises spill over to industries in non-crisis countries through banks operating in both countries. However, banks transmit this spillover effect less to those industries in which they are specialized, as indicated by the positive interaction term ($connected \times SPEC$). For connected countries prone to crisis contagion, increasing industry specialization by one standard deviation increases loan growth to industry i by $(0.11 \times 0.14 =)$ 1.5 %. Thus, this is economically significant as the increase in industry specialization by one standard deviation fully undoes the spillover effect to the connected industry. Similar to the regression at the bank-firm level, horse-racing this coefficient with the interaction effect between *banking crisis* and *industry specialization* in column (3), the effect reduces to $(0.11 \times 0.07 =)$ 0.8 % remaining positive and statistically significant.

Table 10: **Spillover Effects to Industries by Bank Specialization**

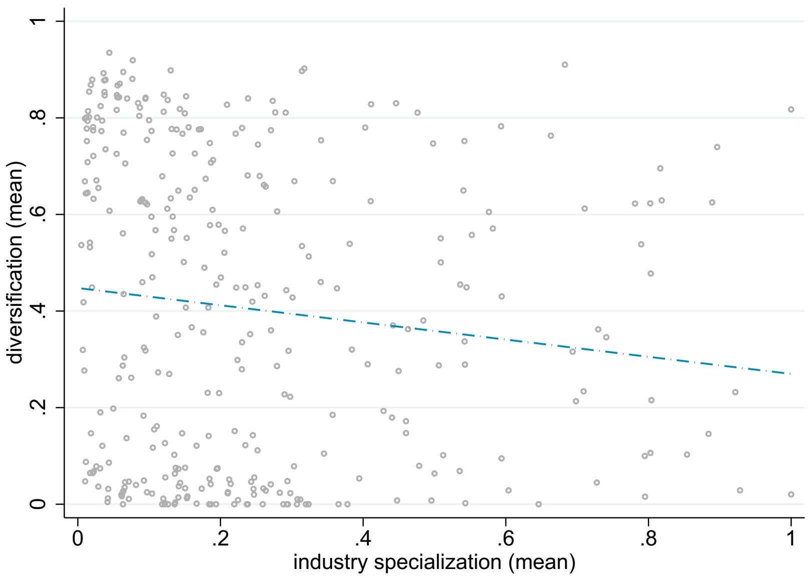
VARIABLES	(1) Δ loan	(2) Δ loan	(3) Δ loan
CON × Industry spec.		0.14***	0.07***
		(0.02)	(0.02)
BC × Industry spec.			0.04*
			(0.02)
Banking crisis (BC)	-0.01***	-0.02***	-0.02***
	(0.01)	(0.01)	(0.01)
Industry spec.			0.31***
			(0.03)
Connected (CON)	-0.01	-0.01**	-0.01*
	(0.00)	(0.00)	(0.00)
Observations	420,334	420,334	420,334
R-squared	0.05	0.05	0.05
Bank*Industry FE	Yes	Yes	Yes
Bank*Time FE	Yes	Yes	Yes
Clustered SE	Bank	Bank	Bank

Note: This table shows regressions on the bank-industry-quarter level. The dependent variable is log of total outstanding loan volume by bank b to firm f in quarter t; *banking crisis (BC)* is a dummy with value one during banking crises in the firm country, as defined in (Laeven2013); *Industry specialization* is measured as the ratio of loans granted by bank b to all borrowers of industry i in time period t relative to bank b's total lending granted in the same period, lagged by one period (quarter). *Connected countries* is a dummy variable which uals one for all non-crisis countries c' ($\neq c$), to which bank b is actively lending in t. *** p<0.01, ** p<0.05, * p<0.1

To sum up, we find that banking crises spill over to other non-crisis countries through cross-border lending. We document that banks reduce lending both to specific borrowers and entire industries in non-crisis countries in response to a banking crisis in one of their active countries. Moreover, banks shield their main industries from this spillover effect as they reduce lending less to those connected industries in which they are specialized in. As a result, industries with lower presence of specialized banks are more prone to banking crisis contagion operating through cross-border lending.

7 Robustness

Figure 5: **Bank Industry Specialization vs. Geographic Diversification**



Note: This figure shows the relationship between bank industry specialization and bank geographic diversification, by plotting their mean values on the bank level. The blue dashed line is a linear fit. Geographic diversification is defined as banks loan portfolio diversification across borrower countries as in Doerr and Schaz (2019). Industry specialization is defined as banks share of loans issued to borrowers of an industry.

A potential source of omitted variable bias arises from alternative measures of bank's portfolio that could potentially be related to industry specialization. For example, Doerr and Schaz (2019) document that bank lending during crises can be explained by geographic diversification of banks, that is, their diversification of lending across multiple borrower countries. It may be that industry specialization and geographic diversification are correlated and that one dimension of a banks business model explains the other. Figure 5 illustrates the relatip between geographic diversification and industry specialization in a scatter plot. The linear fit shows that there is a weak negative correlation between industry specialization and geographic diversification of -0.11. However, this correlation is not statistically different from zero. For illustration, this suggests that a bank may be highly geographically diversified, that is, it lends to multiple borrower countries and at the same time highly specialized in one industry, lending to borrowers of the same industry in multiple countries; scoring high on geographic diversification and high on

TABLE 11: **Banks' Industry Specialization vs. Geographic Diversification**

VARIABLES	(1) log(loan)	(2) log(loan)
BC × Industry spec.		0.47***
		(0.06)
Industry spec.		2.61***
		(0.06)
BC × DIV	0.15***	0.17***
	(0.03)	(0.03)
Banking crisis (BC)	-0.06***	-0.08***
	(0.02)	(0.02)
Observations	795,352	795,352
R-squared	0.95	0.95
Bank*Firm FE	Yes	Yes
Bank*Time FE	Yes	Yes
Clustered SE	Bank	Bank

Note: This table shows regressions on the bank-firm-quarter (loan) level. The dependent variable is log of total outstanding loan volume by bank b to firm f in quarter t; *banking crisis (BC)* is a dummy with value one during banking crises in the firm country, as defined in (Laeven2013); *Industry specialization* is measured as the ratio of loans granted by bank b to all borrowers of industry i in time period t relative to bank b's total lending granted in the same period, lagged by one period (quarter). *Geographic diversification (DIV)* is defined as banks loan portfolio diversification across borrower countries as in Doerr and Schaz (2019), lagged by one period. *** p<0.01, ** p<0.05, * p<0.1

industry specialization. Contrastingly, a bank may be geographically diversified and at the same time diversified across multiple industries, thereby scoring high on geographic diversification and low on industry specialization. This is suggestive evidence that geographic diversification and industry specialization capture different dimensions of banks' business model as they are uncorrelated.

Table 11 tests whether industry specialization can be explained by geographic diversification. In column (1), we find that geographic diversification is positive and significant during banking crises. Moreover, column (2) compares the two coefficients of the interaction terms between industry specialization with banking crises and geographic diversification with banking crises. Results show that coefficients of both geographic diversification and industry specialization remain positive and statistically significant during banking crises. Overall, this provides evidence that lending behaviour by industry specialization during crises cannot be explained by banks' geographic diversification.

8 Conclusion

We conduct a comprehensive analysis of banks industry-specific lending strategies when faced with a banking crisis in a borrower country. We construct a metric to categorize banks according to the industry specialization of their international loan portfolio. For a large sample of cross-country syndicated loans, we find that banks that specialize in certain industries are a resilient source of financing for firms in those industries that experience a countrywide financial crisis. Specialized banks not only stabilize loan supply within affected countries, but also mute spillover effects of the crisis to non-crisis markets. Banks mute the negative supply shock to their main industries by 6.3 % within crisis countries, and by 2.8 % to their main industries in connected non-crisis countries. Detailed loan-level data ensure identification through time-varying fixed effects on the firm level; Robustness tests show that it is unlikely that the results are driven by individual characteristics of the banks', quality of the firms, or bank-firm specific information that they have collected through previous interactions.

Our results indicate the positive aspect of lending concentration during crisis times and contribute to the debate on the costs and benefits of banks' portfolio concentration, by revealing the potentially beneficial impact of portfolio concentration, i.e. industry specialization, on firm loan supply. Our results suggest that specialization of banks' portfolio in one industry increases the resilience of those industries in times of domestic financial crises as well as shields these specialized industries in times of foreign financial crises from cross-border contagion.

Chapter III

The Real Effects of Financial Protectionism

Based on Schaz (2019).

1 Introduction

The collapse of Lehman Brothers in 2008 and the subsequent euro area crisis were followed by a sharp decline in banking integration. Throughout Europe, national policy makers stepped up to help their ailing banks with unprecedented government support. In spite of these attempts to stabilize the banking sector in order to prop up the economy, Europe is looking back on a decade of low growth, low investment, a slow recovery to jobs and cross-border bank flows on the decline.[1]

In this paper, I provide novel evidence on financial protectionism and its real effects on firms using data on almost the entire European banking sector. I define financial protectionism as a change in the preferences of domestic banks, induced by government support that leads them to discriminate against foreign firms.[2] According to anecdotal evidence on financial protectionism, the six French bailout banks committed to maintain domestic lending at a growth rate of $3-4$ %, in return for receiving government support (Woll, 2014, p. 117). To examine financial protectionism empirically, I extend the UK setting in Rose and Wieladek (2014) to all 28 EU countries capturing more than 500 banks. Additionally, I observe changes in political connections, such as a transfer of control rights to uncover the mechanism of financial protectionism. Moreover, I use

[1]For evidence on the decline of cross-border bank flows see Cerutti and Claessens (2016); Bremus and Fratzscher (2015); Bussière, Schmidt and Valla (2018); Emter, Schmitz and Tirpák (2016); European Central Bank (2017)

[2]This definition was proposed by Rose and Wieladek (2014).

bank-firm relationships to identify loan supply and test for real effects at the firm level working through a distortion of credit allocation.

I find that bailout banks increase home bias in lending more than non-bailout banks. Moreover, this increase in home bias is primarily driven by a reduction in foreign lending. In particular, banks increase their home bias by 24.6 % following a bailout from their home government. On the intensive margin, bailout banks increase lending volume to home relative to foreign borrowers by 30.4 % more than non-bailout banks. This lower cross-border loan supply has significant real effects on the performance of foreign firms. Firms at the 90^{th} percentile in terms of dependence on foreign banks affected by a bailout have 6.5 % lower loan growth, relative to firms at the 10^{th} percentile. I find that firms are not able to substitute this reduced access to cross-border lending by other forms of funding, such as non-syndicated loans or corporate bonds. Hence, reduced access to cross-border loans paired with imperfect credit substitution translates into weaker sales (-3.5 %) and employment (-3 %) growth of firms with stronger dependence on foreign bailout banks. In contrast, having a stronger relationship with home banks affected by a bailout has no significant effect on average loan growth or firm performance. Moreover, I document that government support for banks distorts credit allocation by providing more lending to larger, safer and less innovative firms in the protected home market. These findings suggest that government support for banks has discouraged international economic activity, distorted credit towards less productive firms and was harmful to both economic growth and employment.

I provide evidence that governments engage in financial protectionism and that the mechanism operates through a transfer of control rights from bank to government. Results show that preferential lending for home borrowers is strongest when the recapitalization funds of the bailout come in conjunction with a shift of control rights from bank to government. In contrast, bailout banks that receive a recapitalization without a change in control rights do not significantly change their loan mix. This suggests that politicians gain novel influence over bank lending through a transfer of control rights from the bank to the government as part of the bailout.[3] Thus, these findings suggest that governments persuade banks to redirect loan supply towards the home market in return for the bailout, in line with the financial protectionism hypothesis (Rose and Wieladek, 2014).

[3]The importance of political connections for bank bailouts has been shown in Duchin and Sosyura (2012); Chavaz (2016), while Bertrand, Kramarz, Schoar and Thesmar (2018); Goldman, Rocholl and So (2013, 2009); Cheung, Jing, Rau and Stouraitis (2017) highlight importance of political connections more generally. For evidence on home bias and moral suasion in a different market, that is, the market for government bonds see Acharya and Steffen (2015).

The data spans the period from 2000 through 2015, capturing 66 banks that received government support during the Great Financial Crisis. I consider three types of government support for banks: nationalizations, recapitalizations and other (that is, unusual access to liquidity) using data from the European Commission State aid Cases. Moreover, I apply a time-varying ownership correction of more than 2,100 bank subsidiaries to aggregate lending at the bank holding level.[4] This data captures reallocation of credit across countries through subsidiaries using the internal capital market of the bank holding entity. Moreover, I add balance sheet data for both firms and banks, by merging the firm-bank relationship data in Dealscan with Compustat and Bankscope. This information in combination with the granular loan level data allows overcoming challenges to identification common in the literature.[5]

The first identification challenge to establishing loan supply effects is to address firm heterogeneity. The concern is that changes in firm's demand for loans over time may bias the results on bank lending. While this issue cannot be addressed with aggregated data, disaggregated data allows to overcome this. To address the trade-off between identification and external validity, I absorb loan demand at three distinct levels of aggregation. First, I construct a bank-borrower country panel that allows for inclusion of borrower-country-time fixed effects to absorb time-varying changes in loan demand in each borrower country.[6] Second, I move to the firm level where I include firm country-industry-time fixed effects. I use firm fixed effects to base inference on the within firm variation and additionally control for size, performance, leverage and liquidity to capture time-varying firm heterogeneity. Third, I move to the granular bank-firm level to employ firm-time fixed effects. By comparing the lending behavior of bailout and non-bailout banks to the same borrower, I address the concern that differences in loan demand biases the results on bank lending. The negative effect on foreign lending by bailout banks hence reflects loan supply.

The second identification challenge is a likely selection bias into bailout and non-bailout banks. Indeed, bailout and non-bailout banks differ ex-ante in terms of size, global footprint and capitalization. Hence, I address selection bias into bailout and non-bailout banks by implementing propensity score matching on bank observables. After matching bailout and non-bailout banks along their home country, year, total assets, leverage, tier 1 capital ratio, liquidity risk, non-performing loans, return on assets, globalness

[4] I hand-construct the time-varying ownership aggregation as in Schwert (2018).

[5] For a discussion on the common identification challenges on identifying loan supply see Khwaja and Mian (2008); Jiménez, Atif, Peydro and Saurina Salas (2012); Jiménez, Ongena, Peydró and Saurina (2014); Morais, Peydro and Ruiz Ortega (2019).

[6] This specification follows the research design in Giannetti and Laeven (2012)

and political connections – bailouts continue to be associated with a sizable increase in the home bias of lending. Moreover, I test whether bank business models are a potential source of omitted variable bias for bailouts. In particular, both banks with higher geographic diversification and higher industry specialization of their loan portfolio are found to be more stable sources of lending during banking crises, which could in turn affect governments' bailout decisions ex-ante (Doerr and Schaz, 2019; Boskovic, Doerr and Schaz, 2019). I find that neither banks' geographic diversification nor banks' industry specialization increase the bailout proability of banks. Hence, these findings mitigate doubts on omitted variable bias stemming from banks business models.

An alternative explanation is that the reduction in foreign lending following a bailout merely reflects a flight home effect common to all foreign banks (De Haas and Van Horen, 2013). Indeed, I find evidence on a flight home effect across all foreign banks. However, the cross-border loan retrenchment by foreign bailout banks is twice as strong as for foreign non-bailout banks. While this supports the findings in Giannetti and Laeven (2012), it also implies that the flight home effect cannot fully explain the observed contraction in cross-border lending.

This paper contributes to the discussion on the drivers of financial disintegration and the ongoing policy debate on designing the European Banking Union.[7] The results point to the importance of a consistent framework for bank resolution and bank supervision within an economic union. Bank resolution at the national level leads to pro-cyclical banking integration that harms financial stability. In this framework, national policy-makers are incentivized to persuade their banks to protect the local economy causing a welfare loss through the destruction of cross-border bank-firm relationships. Importantly, the cross-border bank retrenchment associated with financial protectionism leads to a capital misallocation that harms both economic growth and employment in the European Union.

2 Data & Empirical Strategy

2.1 Data

I capture lending of almost the entire European banking sector operating on Dealscan during the period from 2000 to 2015. The sample consists of 529 bank holdings headquartered in 28 EU countries. I include all banks with a mean lending volume of larger

[7]For a discussion on retrenchment in financial integration since the Global Financial Crisis see Claessens (2017); Bremus and Neugebauer (2018b).

than 22m USD focusing on lending by commercial banks. Banks are then aggregated at the parent level applying a time-varying ownership correction of each subsidiary during the sample period. I hand-correct changes in the ownership from 2,199 subsidiaries using information on ownership changes from company websites, Bankscope and newspaper articles.[8] Then, I merge the lending banks from Dealscan with Bankscope to add balance sheet information, accounting for time-varying ownership changes throughout the sample.[9]

To construct lending relationships between banks and firms, I use data on syndicated loans from Dealscan. The syndicated loan market accounts for a significant share of total lending. Around one-third of total international lending is done through the syndicated loan market (Gadanecz and von Kleist, 2002) and it is an important source of financing in both developed and emerging economies (Cerutti, Hale and Minoiu, 2015). Syndicated loans are issued jointly by a group of banks to a single borrower. The lending syndicate includes at least one lead bank and usually further participant banks. Lead banks negotiate terms and conditions of deals, perform due diligence, and organize participants. Therefore, lead arrangers stand in direct contact with the borrower and retain larger loan shares for signaling purposes (Saleem Ramadan, 2013). Participants are usually not in direct contact with the borrower, but merely supply credit. Compared to other types of bank loans, syndicated loans are on average larger in volume and issued to bigger borrowers. I restrict the sample to loans by banks to non-financial firms and consider lending only by commercial, savings, cooperative and investment banks.[10] I consider both lending by lead arrangers and participants to capture total loan supply on the syndicated loan market.

Bailout data is hand-collected using the State aid Cases provided by the European Commission.[11] I classify bailouts into three types: nationalization, recapitalization and other (e.g. unusual access to liquidity). Each type is constructed as time-varying dummies that take value one for periods in which the state intervention is active. Therefore, the unit of variation is the bank-bailout country-year level. Start and end dates are

[8]For the time-varying ownership correction I follow Schwert (2018) who presented this correction for the US and apply it to the European banking sector.

[9]For more information on the syndicated loan market's institutional setting see Berg, Saunders and Steffen (2016).

[10]In Dealscan, I include only the lender types Commercial Banks, Finance Companies, Investment Banks, Mortgage Banks, Thrift/S&L, and Trust Companies. Investment banks constitute 3 % of our sample and excluding them does not change results. Borrower types included are Corporations, Insurance Companies, Law Firms, Leasing Companies and Other. See Doerr and Schaz (2019) for further details on data construction using Dealscan data.

[11]The data can be downloaded here: `http://ec.europa.eu/competition/elojade/isef/index.cfm?clear=1&policy_area_id=3`

drawn from the State aid Cases. In case of unknown end dates, the nationalizations will take value one for the full sample period. In case of recapitalizations, I impute the end dates using the average duration of recapitalizations in the sample with known end dates. In addition, I construct the continuous variable 'recapitalization amount' where the full recapitalization amount is spread uniformly across all periods in which the bailout is active. Consecutive interventions are aggregated.

TABLE 1: **Summary Statistics (*bank-level sample*)**

Variable	**Mean**	**Std. Dev.**	**Min.**	**Max.**	**N**
ln(Total assets)	16.688	2.178	10.597	21.965	3395
Total lending in bn USD	8.196	32.91	0	625.198	5229
Leverage in %	91.962	7.744	5.073	100	3389
Tier 1 ratio in %	12.223	6.487	2.02	100	2240
Liquidity risk in %	1.197	3.107	0	90.031	3185
Non-performing loans in %	7.179	9.045	0	95.828	2216
Political Connections $\in \{0, 1\}$	0.4	0.49	0	1	5321
Home share in %	58.285	41.442	0	100	5321
Globalness $\in [1, \infty]$	9.827	17.993	1	94	5321

Note: This table shows summary statistics of variables at the *bank-year-level*. *Total lending*$_{b,t}$ (in bn USD) is bank b's total outstanding lending volume on the syndicated loan market in year t. *Leverage*$_{b,t}$ is bank b's leverage in year t. *Tier 1 ratio*$_{b,t}$ is bank b's tier 1 capital ratio in year t. *Liquidity risk*$_{b,t}$ is the ratio of total loans to deposits plus short-term liability claims. *Non-performing loans*$_{b,t}$ is the ratio of non-performing loans (NPL) to total loans (including syndicated and non-syndicated lending). *Political Connections*$_{b,t}$ is a dummy with value one if the home government has a positive ownership share in bank b. *Home share*$_{b,t}$ is bank b's ratio of home loans to total loans on the syndicated loan market. *Globalness*$_{b,t}$ is defined as bank b's number of active borrower countries on the syndicated loan market in year t.

I obtain balance sheet data of banks by merging lenders active in Dealscan with Bankscope. Overall, I am able to match 466 non-bailout banks and 66 bailout banks in the sample. Summary statistics for the bank-level sample are displayed in Table 1. The average bank has an outstanding loan volume of 8.2 bn USD, a leverage of 92 % and is active in 10 borrower countries. Table 2 splits the sample into bailout and non-bailout banks and shows that these two groups are quite heterogeneous. Bailout banks are on average larger, are more leveraged, have more non-performing loans, more political connections[12] and a stronger global footprint. This highlights the importance

[12]Measured as government bank ownership compiled from Bankscope

of addressing this heterogeneity in the identification strategy in order to reduce the likelihood that results are driven by omitted factors that are specific to bailout banks vis-a-vis non-bailout banks.

TABLE 2: **Bailout vs. Non-Bailout Banks (*bank-level sample*)**

	Bailout Banks		**Non-Bailout Banks**		**Mean Diff**
	mean	sd	mean	sd	t
ln(Total assets)	18.24	(1.70)	16.56	(2.16)	-12.16
Total lending in bn USD	33.63	(63.29)	6.74	(29.61)	-13.63
Leverage in %	93.77	(4.39)	91.81	(7.94)	-3.90
Tier 1 ratio in %	11.96	(4.39)	12.25	(6.66)	0.60
Liquidity risk in %	0.96	(0.66)	1.22	(3.23)	1.29
Non-performing loans in %	12.81	(12.56)	6.54	(8.32)	-10.10
Political Connections $\in \{0, 1\}$	0.58	(0.49)	0.39	(0.49)	-6.37
Home share in %	46.24	(37.42)	58.98	(41.56)	5.11
Globalness $\in [1, \infty]$	25.44	(27.81)	8.92	(16.82)	-15.57

Note: This table shows summary statistics for bailout and non-bailout banks separately for variables at the *bank-year-level.* There are a total of 66 bailout banks and 466 non-bailout banks. *Total lending*$_{b,t}$ (in bn USD) is bank b's total outstanding lending volume on the syndicated loan market in year t. *Leverage*$_{b,t}$ is bank b's leverage in year t. *Tier 1 ratio*$_{b,t}$ is bank b's tier 1 capital ratio in year t. *Liquidity risk*$_{b,t}$ is the ratio of total loans to deposits plus short-term liability claims. *Non-performing loans*$_{b,t}$ is the ratio of non-performing loans (NPL) to total loans (including syndicated and non-syndicated lending). *Political Connections*$_{b,t}$ is a dummy with value one if the home government has a positive ownership share in bank b. *Home share*$_{b,t}$ is bank b's ratio of home loans to total loans on the syndicated loan market. *Globalness*$_{b,t}$ is defined as bank b's number of active borrower countries on the syndicated loan market in year t.

Bank-borrower country level I construct the bank-borrower country level from data on syndicated lending. First, I decompose syndicated loan deals into loan portions provided by each lender to obtain granular credit level data. Whenever Dealscan provides information on lending shares of each bank, I use this information to split loan volume accordingly (available for 28 % of the deals).[13] In cases where lending shares are missing I split loan volume on a pro-rata basis among all banks in a syndicate.[14] Transactions with deal status 'canceled', 'suspended', or 'rumor' are removed and all loan nominations

[13]See Giannetti and Laeven (2012); De Haas and Van Horen (2013)

[14]In the sub-case of partial information on loan shares, I first use the available information to allocate loan shares. Then, I split the remaining amount equally among banks with missing information. If the sum of the allocation rule is larger than 110 % I consider this an erroneous entry and treat it as if lending share information was not available in the first place.

TABLE 3: **Summary Statistics (*bank-borrower country-level sample*)**

Variable	Mean	Std. Dev.	Min.	Max.	N
ln(Loan volume)	4.634	1.86	0.224	10.471	51272
Lending bias $\in [-1, 1]$	0.159	0.657	-0.986	0.999	51281
ln(Total assets)	18.928	1.858	12.354	21.965	33379
Leverage in %	94.281	4.943	16.029	100	33650
Tier 1 ratio in %	11.822	9.415	3.4	100	27558
Liquidity risk in %	1.172	3.191	0	90.031	30927
Non-performing loans in %	5.564	5.492	0.129	45.176	25607
Bailout $\in \{0, 1\}$	0.142	0.349	0	1	52289
Control Rights Transfer $\in \{0, 1\}$	0.036	0.187	0	1	52289
Political Connections $\in \{0, 1\}$	0.368	0.482	0	1	52289
Globalness $\in [1, \infty]$	42.766	27.394	1	94	52289

Note: This table shows summary statistics of variables at the *bank-borrower country-year-level*. *ln(Loan volume)*$_{b,j,t}$ is the log of bank b's outstanding lending volume to all borrowers in country j on the syndicated loan market in year t. *Lending bias*$_{b,j,t}$ is the lending bias of bank b to all borrowers from country j at time t as defined in Section 2. *Leverage*$_{b,t}$ is bank b's leverage in year t. *Tier 1 ratio*$_{b,t}$ is bank b's tier 1 capital ratio in year t. *Liquidity risk*$_{b,t}$ is the ratio of total loans to deposits plus short-term liability claims. *Non-performing loans*$_{b,t}$ is the ratio of non-performing loans (NPL) to total loans (including syndicated and non-syndicated lending). *Bailout*$_{b,t}$ is a dummy with value one if bank b receives a bailout in year t. *Control Rights Transfer*$_{b,t}$ is a dummy with value one if the bailout of bank b is a nationalization. *Political Connections*$_{b,t}$ is a dummy with value one if the home government has a positive ownership share in bank b. *Globalness*$_{b,t}$ is defined as bank b's number of active borrower countries on the syndicated loan market in year t.

transformed into million U.S. Dollars (USD) using the spot exchange rate at origination, provided by Dealscan. If after this allocation procedure the loan portion is smaller than 10,000 USD, I drop the observation to remove erroneously small loans (0.6 % of observations). Next, I use the loan portions to construct each bank's outstanding loan volume as a stock variable to proxy the loan's entry on the loan book (Morais, Peydro and Ruiz Ortega, 2019). Each outstanding loan remains active until the end of its maturity. Second, I aggregate all outstanding loan portions between a bank-firm combination to obtain bank b's outstanding loan volume to firm f in year t, forming a bank-firm-year observation. Third, I aggregate all bank-firm-year observations by firm (borrower) country to obtain the bank-borrower country-year level as in Giannetti and Laeven (2012). Thus, I obtain each bank b's log outstanding lending volume to all borrowers of country j ($volume_{b,j,t}$). Table 3 shows summary statistics at the bank-borrower country-level.

I construct a bias metric to take into account that time-varying differences in the borrower countries' market sizes may drive changes in bank lending shares. This bias metric captures the lending bias of bank b to all borrowers from country j at time t. Following Bremus and Fratzscher (2015), I adopt the bilateral bias definition to the bank-borrower country level:

$$bias_{b,j,t} = \begin{cases} \frac{s_{b,j,t}-w_{j,t}}{w_{j,t}} & \text{if } s_{b,j,t} \leq w_{j,t} \\ \frac{s_{b,j,t}-w_{j,t}}{s_{b,j,t}} & \text{if } s_{b,j,t} > w_{j,t}, \end{cases} \tag{1}$$

bounding the bias between $[-1, 1]$ as in Bremus and Fratzscher (2015) in order to avoid outliers to drive results. Where $s_{b,j,t}$ denotes bank b's lending share to all borrowers of country j, and $w_{j,t}$ is the market share of country j in the global syndicated lending market. All shares are time-varying at annual frequency denoted with t. Intuitively, a bias value of larger than zero implies that bank b's share in market j is larger than market j's share in the total syndicated loan market. Thus, positive (negative) values of $bias_{b,j,t}$ imply a positive (negative) bias to borrowers in the respective country, relative to the market size of this country.[15]

Firm level In order to analyze the effects of loan supply on firm (borrower) performance, I add firm balance sheet information to the data constructing a firm-year level. To do so, I first aggregate the firm-bank-year loan data to the firm-year level to obtain firms' lending relationships. Second, I match firms (borrowers) in Dealscan with firms in Compustat (Global and US) using the linking file used in Chava and Roberts (2008) and updated as of April 2018. Overall, I am able to match 8,205 firms (33 % of all firms) borrowing from 463 banks (161,645 firm-year observations). Summary statistics at the firm-level are shown in Table 4. This linking exercise gives rise to a selection bias into larger firms that are less financially constrained. Thus, I expect this selection bias to render the estimates of the real effects to become more conservative. The reason being that the effect of a negative loan supply shock on firm performance is found to be larger for smaller firms with less financial leeway in previous studies (Cohen and Pascaline, 1997).

To measure firms' relationships with banks that differ in the two dimensions of interest – nationality and bailout treatment – I construct three variables. These variables capture the differential lending effects by the four bank types on firm outcomes. First, *foreign affected* measures a firms relationship with foreign banks that are affected by a

[15] Note, that due to this normalization between $[-1, 1]$, the mean bias is $\neq 0$ in Table 3.

Table 4: **Summary Statistics (*firm-level sample*)**

Variable	Mean	Std. Dev.	Min.	Max.	N
Foreign affected $\in [0,1]$	0.151	0.295	0	1	161645
Foreign unaffected $\in [0,1]$	0.631	0.413	0	1	161645
Home affected $\in [0,1]$	0.037	0.142	0	1	161645
Δ loan volume	0.02	0.327	-1.535	5.109	132931
Δ long-term debt	0.075	0.554	-3.03	3.034	53146
Δ sales	0.07	0.201	-1.545	1.093	53311
Δ employment	0.031	0.168	-0.865	0.87	44844
ln(Total assets)	8.433	2.032	3.516	16.381	57394
Leverage in %	32.943	19.464	0	135.108	57648
ln(Sales)	7.993	2.235	-5.116	23.464	56449
Liquidity in %	0.001	2.968	-464.512	94.8	54925
ln(Common equity)	7.395	2.254	-4.51	22.548	55601

Note: This table shows summary statistics of variables at the *firm-year-level*. $foreign\ affected_{f,t-1}$ is the share of firm f's outstanding loan volume coming from foreign banks affected by a bailout at t. $foreign\ unaffected_{f,t-1}$ is the share of loans coming from banks unaffected by a bailout. $home\ affected_{f,t-1}$ is the share of firm f's outstanding loan volume coming from home banks that received by a bailout at t. $\Delta loan\ volume_{f,t}$ is the log difference of firm f's total borrowing on the syndicated loan market. $\Delta long\text{-}term\ debt_{f,t}$, $\Delta sales_{f,t}$ and $\Delta employment_{f,t}$ is the log difference of firm f's long-term debt, sales and employment respectively. $\Delta Liquidity_{f,t}$ (in %) is the ratio of firm f's cash flows over total assets.

bailout. Intuitively, a high value of *foreign affected* implies that a firm borrows a lot from foreign banks that receive a bailout. I construct this metric as the share of loans coming from banks that are affected by a bailout at t ($BO_{b,t} = 1$) and are foreign relative to the firm's nationality by headquarter ($foreign_b = 1$):

$$foreign\ affected_{f,t} = \frac{\sum_{\forall b} loan_{f,b,t} \cdot BO_{b,t} \cdot foreign_b}{\sum_{\forall b} loan_{f,b,t}} \tag{2}$$

Intuitively, *foreign affected* $= 1$ implies that a firm borrows exclusively from foreign banks that are all affected by a bailout. While a firm with *foreign affected* $= 0$ has no relationship with a bank that is affected by a bailout at time t. Therefore, higher values of *foreign affected* imply a stronger relationship of a firm with foreign banks that are affected by a bailout. The average firm has 15.1 % of loans outstanding from foreign bailout banks, as can be seen from Table 4.

$$foreign\ unaffected_{f,t} = \frac{\sum_{\forall b} loan_{f,b,t} \cdot NOBO_{b,t} \cdot foreign_b}{\sum_{\forall b} loan_{f,b,t}} \tag{3}$$

Table 5: **Summary Statistics (*bank-firm-level sample*)**

Variable	Mean	Std. Dev.	Min.	Max.
ln(Loan volume)	3.771	1.35	0.122	7.045
Foreign $\in \{0,1\}$	0.768	0.422	0	1
Bailout $\in \{0,1\}$	0.184	0.387	0	1
N		563199		

Note: This table shows summary statistics of variables at the *bank-firm-year-level* (or *loan-level*). *ln(Loan volume)*$_{b,f,t}$ is log of bank b's outstanding lending volume to borrower f in year t. *Foreign*$_{f,t}$ is a dummy with value one if firm f's nationality is different from bank b, by headquarter location. *Bailout*$_{b,t}$ is a dummy with value one if bank b receives a bailout in year t.

Second, *foreign unaffected* captures firms' relationships with foreign banks that are unaffected by a bailout. Third, *home affected* measures firms' relationships with banks from its home country that receive a bailout from the home government. Respectively, I weigh a firm f's outstanding loan volume by the bank dummies foreign ($foreign_b = 1$), affected ($BO_{b,t} = 1$) and unaffected ($NOBO_{b,t} = 1$):

$$home\ affected_{f,t} = \frac{\sum_{\forall b} loan_{f,b,t} \cdot BO_{b,t} \cdot home_b}{\sum_{\forall b} loan_{f,b,t}} \tag{4}$$

The relationship between Equation (2) and (4) is that they split a firms' relationships with bailout banks into home and foreign. Table 4 shows that the average firm has 63.1 % of loans outstanding from foreign non-bailout banks and 3.7 % from home bailout banks. The remaining fourth variable capturing a firms' relationship with home non-bailout banks is omitted and will be the control group in the regression analysis.

2.2 Empirical Strategy

Bank-borrower country level According to the financial protectionism hypothesis, banks are persuaded by the national government to shift lending towards the home market in return for receiving a bailout (as in Rose and Wieladek (2014); Chavaz (2016)). To test this hypothesis, I start by exploring how bank b's propensity to lend borrowers in country j at year t varies, depending on whether country j is the bank's home country and whether bank b receives a bailout or not. Therefore, the baseline regression specification is:

$$y_{b,j,t} = \beta_1\ home_{b,j} \times BO_{b,t} + \beta_2\ home_{b,j} + \beta_3\ BO_{b,t} + X_{b,t-1} + \mu_{b,j} + \theta_{b\times t} + \phi_{j\times t} + \varepsilon_{b,j,t}, \tag{5}$$

where the dependent variable, $y_{b,j,t}$, is either the outstanding loan volume by bank b to borrowers in country j at year t ($volume_{b,j,t}$), or the bias of bank b's loan portfolio to borrowers from country j at year t ($bias_{b,j,t}$). The dependent variable $volume_{b,j,t}$ thus captures effects on the intensive lending margin; while $bias_{b,j,t}$ captures effects on a banks' lending bias by taking time-varying changes of borrower country market j's size into account. On the right hand side of the equation, $home_{b,j}$ is a time-invariant dummy taking value one if country j is bank b's home country by headquarter location. The bailout dummy variable $BO_{b,t}$ takes value one if bank b receives a bailout at time t.[16] $X_{b,t-1}$ denotes following bank-year control variables to capture omitted variables: assets, leverage, tier 1 capital ratio, non-performing loans, liquidity risk and globalness (number of bank b's active countries j) lagged by one period. $\theta_{b\times t}$, $\phi_{j\times t}$, and $\mu_{b,j}$ denote bank-time, borrower country-time and bank-borrower country fixed effects, respectively. Standard errors are clustered at both the bank and time level.

The coefficient of interest is β_1, which reflects to what extent a bailout increases the bank's propensity to grant new loans to home rather than to foreign borrowers. According to the financial protectionism hypothesis, I expect $\beta_1 > 0$. That is, a bank increases its lending volume or lending bias at home more than abroad, following a bailout.

Central to the estimation of equation (5) is the definition of the control group. That is, for which observations the bailout variable $BO_{b,t}$ takes value zero. It takes value zero for all banks that do not receive a bailout, which assumes that all banks in the sample not receiving a bailout are a reasonable counterfactual for the treatment variable bailout. However, I draw solely on the within bank or within bank-borrower country variation for estimation to avoid cross-sectional inference from different banks or different bank-country combinations (through bank and bank-borrower country fixed effects).

The first identification challenge to testing the financial protectionism is to absorb loan demand. The granular structure of the underlying loan-level data allows to address this in three steps. First, $\phi_{j\times t}$ capture all time-varying unobserved heterogeneity at the borrower country level, including a borrower country's demand for loans. Second, $\theta_{b\times t}$ capture all time-varying unobserved heterogeneity across banks. For instance, $\theta_{b\times t}$ controls for idiosyncratic shocks to banks' credit supply and other changes at the bank-time level. Third, adding $\mu_{b,j}$ controls for unobservable heterogeneity at the bank-borrower country level such as distance.

[16] Note two things on the construction of the bailout variable. First, the bailout can come from any country. Thus, the bailout country may be different from the bank's home country in a few cases, for example Dexia. Second, the bailout keeps value one for all years in which the bailout is active. It takes value zero, after a bailout ends (for instance, after the scheduled payback of the recapitalization funds).

The second identification challenge is that bailouts are endogenous to other unobservable variables such as political connections. This selection bias may lead to biased coefficients. In Section 3.2, I address concerns on selection bias using propensity score matching on observable variables such as balance sheet characteristics and political connections. Furthermore, I address firm heterogeneity by constructing a granular bank-firm-year panel to employ firm-time fixed effects in the spirit of Khwaja and Mian (2008).[17]

Overall, the employed fixed effects structure allows addressing a range of alternative explanations, to rule out remaining concerns on a potentially spurious correlation between bailouts and a bank's propensity to prefer home over foreign borrowers. Central to the identification is the absorption of any demand shock affecting country j and any supply shock affecting bank b at time t. Thus, the empirical framework allows for identification of the differential propensity of bank b to lend to their home country rather than to a foreign country after receiving a bailout, using as controls other banks that are lending to the same countries but were not bailed out.

Firm level To analyze the effects of credit supply on real effects, I will now move to the firm-year level. I will test whether firms with exposure to foreign bailout banks experience a credit crunch and whether this affects firm performance. To establish real effects of financial protectionism I will proceed in three steps. First, I analyze whether there is a credit crunch for foreign firms following the bailouts. Second, I test whether firms are able to substitute this fall in credit with alternative funding sources. For instance, some firms may be able to draw credit from a bailout bank in its home country. Moreover, firms may also be able to substitute into alternative debt instruments such as non-syndicated loans or corporate bonds. Third, I will test whether imperfect credit substitution leads to real effects for firms.

The key challenge to the identification of financial protectionism is to disentangle two forces intrinsically related to bailouts: financial protectionism and idiosyncratic bank shocks. It may well be, that the discrimination against foreign borrowers is caused by the banks idiosyncratic shock putting the bank into distress in the first place. The comparison of firms' dependence on foreign bailout banks (*foreign affected*) with their dependence on home bailout banks (*home affected*) allows disentangling these two effects; both variables capture firm dependence on bailout banks, while dividing the effect into home bailout banks and foreign bailout banks. If the bailout banks' initial problems

[17] Further studies identifying loan supply effects using firm-time fixed effects are Jiménez, Ongena, Peydró and Saurina (2014) and Morais, Peydro and Ruiz Ortega (2019).

are the cause of the fall in lending, then both foreign and home firms should be equally affected by the negative loan supply effect. If, on the other hand, the reason behind the reduction in lending is, indeed, protectionism associated with the bailout then foreign firms should be stronger affected than home firms by the reduction in lending.

In order to test for a credit crunch, credit substitution and real effects I estimate variants of following regression equation at the firm-year level:

$$\begin{aligned}\Delta\ y_{f,t} = \delta_1\ \textit{foreign affected}_{f,t-1} + \delta_2\ \textit{foreign unaffected}_{f,t-1} \\ + \delta_3\ \textit{home affected}_{f,t-1} + X_{f,t-1} + \phi_f + \phi_{c,i,t} + u_{f,t}\end{aligned} \tag{6}$$

The baseline specification tests for a foreign credit crunch associated with bailouts on the syndicated loan market. Therefore, the dependent variable $\Delta\ y_{f,t}$ will be the loan growth of total syndicated lending by firm f at year t. In the second specification, the dependent variable will be loan growth of total long-term debt of firm f to capture credit substitution into alternative debt instruments such as non-syndicated credit or corporate bonds. To analyze real effects, I use sales and employment growth as dependent variables. The variable *foreign affected*$_{f,t-1}$ is the share of firm f's outstanding credit from foreign banks affected by a bailout as defined in equation (2), with lending relationships lagged by one period. Moreover, *foreign unaffected*$_{f,t-1}$ captures a firm's relationship with foreign banks unaffected by a bailout and *home affected*$_{f,t-1}$ captures a firm's relationship with home banks affected by a bailout, as defined in equations (3) and (4). The redundant variable is a firm's relationship with home banks that are unaffected by a bailout and, hence, forms the control group. $X_{f,t-1}$ denotes following firm-year control variables to capture firm demand: log of total assets, leverage, sales, liquidity and common equity, lagged by one period. ϕ_f denote firm fixed and $\phi_{c,i,t}$ denote country*industry*year fixed effects, where c stands for country and i for industry of firm f.

The main coefficient of interest δ_1 is on *foreign affected* and is the firm-level flip side of β_1, which is the estimated interaction coefficient ($home \times BO$) from bank-country level equation (5). It illustrates the change in loan growth for firms with high dependence on foreign bailout banks capturing the credit crunch of foreign firms. To analyze whether bailouts affect lending to home and foreign firms differently, I add the two control groups: i) *foreign unaffected* to capture a firm's dependence on foreign banks that are unaffected by bailouts, and ii) *home affected* to capture a firm's dependence on home banks that are affected by bailouts. Additionally, this specification sheds light on whether banks increase their home bias by cutting lending to foreign firms or rather by extending more of the new capital to home firms. To avoid contemporaneous effects of bailouts on firms' bank relationships, I include these variables in lags.

In case of perfect substitution, $\delta_1 = 0$ in the regressions with total syndicated lending and long-term debt as dependent variables as firms substitute the fall in lending by switching banks or resorting to non-syndicated debt instruments. For instance, if bailout banks in the home market retrench just as foreign banks shift their business into their own domestic markets, firms switch to home banks leaving net credit unaffected. However, this may not be possible as home banks are at an informational disadvantage relative to foreign banks who had formed lending relationships with the firms. A common finding in the literature is that it is difficult for firms to form new bank relationships in times of banking crises (Smith, Ongena and Smith, 2016; Cohen and Pascaline, 1997). This gives rise to imperfect credit substitution, implying $\delta_1 < 0$.

In order to interpret the estimated coefficients as a loan supply effect, I use firm fixed effects and country*industry*time fixed effects to absorb time-varying loan demand per country-industry bucket. This assumes that all firms in the same country-industry bucket change their loan demand similarly. Alternatively, I will use country*time fixed effects as a less demanding specification and show that results are similar across different specifications. As loan demand may still vary for different firms in each country-industry bucket, I will validate this assumption at the bank-firm-year level using firm*time fixed effects in Section 3.2, as this specification is commonly interpreted as a loan supply effect (Khwaja and Mian, 2008; Jiménez, Ongena, Peydró and Saurina, 2014; Morais, Peydro and Ruiz Ortega, 2019). I will show that results are robust to this rigorous specification.

3 Main Results

I present the main results in four steps. First, I establish evidence on financial protectionism by analyzing bank lending at the bank-borrower country level and show that banks increase their home bias following a bailout (section 3.1). Thereafter, I examine the robustness of the results (section 3.2). Then, I evaluate real effects by showing that firms with higher dependence on foreign bailout banks have lower loan, long-term debt, sales and employment growth (section 4). Finally, I examine the characteristics of the protected home firms and illustrate that lending shifts towards larger, safer and less innovative firms at home (section 5).

3.1 Effect of Bailouts on Lending

Table 6 reports results for regression Equation (5) and shows that banks increase their home bias following a bailout. The dependent variable is the bias of bank b's lending to borrowers from country j at time t as defined in Equation (1). Column (1) looks at the within-bank and within-time variation by using bank and time fixed effects. To control for bank heterogeneity I add size, leverage, capitalization, non-performing loans, liquidity risk and globalness, which restricts the sample to observations with full data coverage in Bankscope. In line with expectations, the coefficient on $Home$ is positive, reflecting the positive home bias in bank lending throughout the sample. The coefficient of interest (β_1) on the interaction term (Home $\times$ Bailout) is positive and statistically significant. Following a bailout, banks increase the lending bias to their home market by ($\frac{0.177}{0.656+0.177}$ =) 21.2 %.

To address concerns about omitted variables, column (2) adds bank-time fixed effects to control for time-varying unobserved heterogeneity across banks. Thus, bank-time fixed effects capture idiosyncratic shocks to banks' credit supply and other changes at the bank-time level. As bank-time fixed effects subsume the bank control variables used in the first specification, this now allows for an analysis on the full sample. Thus, the tendency of bailout banks to lend more to their home country does not depend on the fact that certain banks lend more or less than others to all countries, as I include bank-time fixed effects.

To address time-varying changes in loan demand across countries, I further add borrower country-time fixed effects in column (3). That is, borrower country-time fixed effects control for changes in loan demand at the borrower country level that is common to all banks. Therefore, the tendency of bailout banks to increase their home bias is also not driven by countries rolling out a bailout scheme to borrow more, as the estimates are robust to including borrower country-time fixed effects. In this preferred specification, banks increase the lending bias to their home market by ($\frac{0.253}{0.773+0.253}$ =) 24.6 %, after receiving a bailout.

The coefficient of interest on the interaction term $Home \times Bailout$ remains significant even after controlling for bank-borrower country fixed effects in column (4). This specification relies on the within bank-borrower country variation and thereby controls for further unobservable heterogeneity such as distance between bank and borrower country. The estimated coefficient is now smaller but remains both economically and statistically significant.

TABLE 6: **Effect of Bailouts on Home Bias in Lending**

VARIABLES	(1) Bias	(2) Bias	(3) Bias	(4) Bias
Home × Bailout	0.177**	0.214***	0.253***	0.144**
	(0.0784)	(0.0727)	(0.0660)	(0.0500)
Home	0.656***	0.578***	0.773***	
	(0.0470)	(0.0339)	(0.0338)	
Bailout	-0.0184			
	(0.0216)			
Assets	0.0346			
	(0.0285)			
Leverage	-0.156			
	(0.531)			
Capital ratio	-0.000355			
	(0.00165)			
NPL share	-0.0596			
	(0.174)			
Liquidty Risk	0.00321			
	(0.00530)			
Globalness	-0.00146			
	(0.00194)			
Observations	21,775	48,526	48,526	48,526
Bank FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Bank x Time FE	No	Yes	Yes	Yes
Borrower country x Time FE	No	No	Yes	Yes
Bank x Borrower country FE	No	No	No	Yes
Cluster	Bank + Time	Bank + Time	Bank + Time	Bank + Time

Note: This table shows regressions on the bank-borrower country-year level. The dependent variable is lending bias of bank b to country j at year t as defined in Section 2. $Home_{b,j}$ is a dummy with value one for the banks home country. *Bailout* is a time-varying dummy with value one during active bank bailouts as defined in Section 2. $Leverage_{b,t-1}$ is bank b's leverage in year $t-1$. $Tier\ 1\ ratio_{b,t-1}$ is bank b's tier 1 capital ratio in year $t-1$. $Liquidity\ risk_{b,t-1}$ is the ratio of total loans to deposits plus short-term liability claims, lagged by one year. $Non\text{-}performing\ loans_{b,t-1}$ is the ratio of non-performing loans (NPL) to total loans (including syndicated and non-syndicated lending), lagged by one year. $Globalness_{b,t-1}$ is defined as bank b's number of active borrower countries on the syndicated loan market in year $t-1$. For further details on the variables see Table 3. All standard errors are clustered both at the bank and year level. *** p<0.01, ** p<0.05, * p<0.1

To explore the intensive margin of foreign bank lending following bailouts, I now re-estimate Equation (5), after replacing the dependent variable by the log outstanding loan volume issued by bank b to borrowers in country j at year t. Table 7 shows results on the intensive margin by repeating the identification strategy of Table 6. The coefficient of interest on the interaction term *Home* × *Bailout* is positive and statistically significant across specifications. In the most conservative specification shown in column (4), banks increase the lending volume to borrowers in their home country by 30.4 % relative to foreign borrowers, after receiving a bailout.

TABLE 7: **Effect of Bailouts on Lending Volume**

	(1)	(2)	(3)	(4)
VARIABLES	log loan volume	log loan volume	log loan volume	log loan volume
Home × Bailout	0.630**	0.650**	0.579**	0.304*
	(0.249)	(0.282)	(0.231)	(0.163)
Home	2.814***	2.509***	2.061***	
	(0.139)	(0.108)	(0.0965)	
Bailout	-0.00623			
	(0.0708)			
Assets	0.116			
	(0.0788)			
Leverage	1.221			
	(1.261)			
Capital ratio	0.00196			
	(0.00426)			
NPL share	-0.388			
	(0.459)			
Liquidty Risk	-0.00248			
	(0.00348)			
Globalness	0.0102			
	(0.00593)			
Observations	21,661	48,539	48,539	48,539
Bank FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Bank x Time FE	No	Yes	Yes	Yes
Borrower country x Time FE	No	No	Yes	Yes
Bank x Borrower country FE	No	No	No	Yes
Cluster	Bank + Time	Bank + Time	Bank + Time	Bank + Time

Note: This table shows regressions on the bank-borrower country-year level. The dependent variable is the log outstanding loan volume of bank b to borrowers in country j at year t. $Home_{b,j}$ is a dummy with value one for the banks home country. *Bailout* is a time-varying dummy with value one during active bank bailouts as defined in Section 2. $Leverage_{b,t-1}$ is bank b's leverage in year $t-1$. $Tier\ 1\ ratio_{b,t-1}$ is bank b's tier 1 capital ratio in year $t-1$. $Liquidity\ risk_{b,t-1}$ is the ratio of total loans to deposits plus short-term liability claims, lagged by one year. $Non\text{-}performing\ loans_{b,t-1}$ is the ratio of non-performing loans (NPL) to total loans (including syndicated and non-syndicated lending), lagged by one year. $Globalness_{b,t-1}$ is defined as bank b's number of active borrower countries on the syndicated loan market in year $t-1$. For further details on the variables see Table 3. All standard errors are clustered both at the bank and year level. *** p<0.01, ** p<0.05, * p<0.1

Overall, this suggests that banks are persuaded by the government to engage in financial protectionism in return for receiving a bailout. Across specifications, I find that banks increase their home bias following a bailout. Moreover, bailout banks increase the lending volume more to home borrowers than to foreign borrowers, relative to non-bailout banks. These results hold after controlling for loan demand, bank-borrower country characteristics and time-varying bank heterogeneity.

3.2 Robustness

In this section I address doubts on identification arising due to concerns that bailouts are likely endogenous. First, I address the concern of firm heterogeneity between bailout and non-bailout banks by employing firm-time fixed effects on the firm-bank-time level. Second, I will turn to the issue of selection bias by applying propensity score matching to make bailout and non-bailout banks comparable on observable variables.

The central identification challenge is to identify loan supply to foreign firms following a bailout. It may be that bailout banks are cutting credit more to foreign firms because the quality of their foreign loan portfolio is lower in comparison to non-bailout banks. Hence, firm heterogeneity could explain the differences in lending between bailout and non-bailout banks.

To address this concern, I will move the analysis to the bank-firm-year level in order to absorb loan demand through firm-time fixed effects. By comparing the lending behavior of bailout and non-bailout banks to the same borrower, I address the concern that differences in loan demand biases the results on bank lending (Khwaja and Mian, 2008).

Table 8 shows that bailout banks reduce their lending to foreign firms, relative to non-bailout banks after absorbing loan demand. The dependent variable is the log outstanding loan volume between bank b and firm f at year t. Column (1), adds bank-firm fixed effects to compare the lending of the same banks to the same firm over time.[18] In general, bailout banks extend loans with higher volume, as indicated by the positive coefficient on *Bailout*. The coefficient of interest on the interaction term (*Foreign* $\times$ *Bailout*), however, is highly significant and negative. This supports the previous finding that bailout banks reduce their lending to foreign firms compared to non-bailout banks.

Firm Heterogeneity

To ensure that this negative effect on foreign lending reflects loan supply, column (2) and column (3) add country-industry-time and firm-time fixed effects. Therefore, column (3) supports that the negative effect of bailouts on foreign lending reflects loan supply, as it absorbs any time-varying changes in loan demand at the firm level. Following a bailout, banks reduce their lending volume to foreign firms by 7.2 % relative to non-bailout banks.

In order to control for time-varying differences across banks driven by factors at the bank level, I add bank-time fixed effects in column (4) and (5).[19] In the strictest

[18] The coefficient $Foreign_{b,f}$ is absorbed by bank-firm fixed effects.

[19] The coefficient on $Bailout_{b,t}$ gets absorbed through bank-time fixed effects.

TABLE 8: **Firm Heterogeneity: Firm×Time Fixed Effects**

VARIABLES	(1) log loan volume	(2) log loan volume	(3) log loan volume	(4) log loan volume	(5) log loan volume
Foreign × Bailout	-0.089**	-0.079***	-0.072***	-0.073***	-0.030*
	(0.038)	(0.020)	(0.020)	(0.025)	(0.017)
Bailout	0.252***	0.060***	0.060***		
	(0.041)	(0.019)	(0.019)		
Observations	483,176	483,176	483,176	483,176	483,176
R-squared	0.875	0.925	0.948	0.888	0.951
Bank × Firm FE	Yes	Yes	Yes	Yes	Yes
Bank × Time FE	No	No	No	Yes	Yes
Country × Industry × Time FE	No	Yes	-	No	-
Firm × Time FE	No	No	Yes	No	Yes
Cluster	Country × Time	Country × Time	Country × Time	Country × Time	Country × Time

Note: This table shows regressions on the bank-firm-year level. The dependent variable is the log outstanding loan volume of bank b to borrowers f at year t; $Foreign_{b,f}$ is a dummy with value one if firm f has a different nationality than bank b; *Bailout* is a time-varying dummy with value one during active bank bailouts as defined in Section 2. For further details on the variables see Table 5. All standard errors are clustered both at the bank and year level. *** p<0.01, ** p<0.05, * p<0.1

specification reported in column (5), the magnitude of the coefficient is reduced but remains both statistically and economically significant at 3 %.

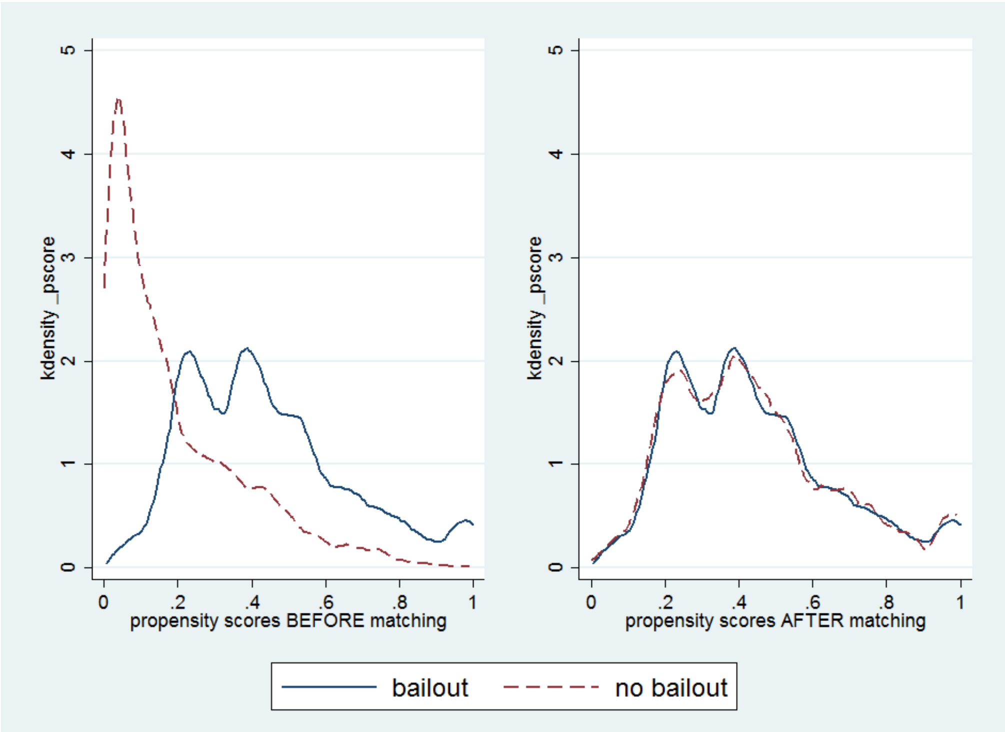
Comparing column (2) and (3), both country-industry-time and firm-time fixed effects yield similar coefficients. This similarity supports the identification strategy at the firm level in section 4, where aggregation allows only the inclusion of country-industry-time fixed effects.

Overall, these results confirm the previous finding on bailouts and foreign lending: banks reduce their lending to foreign firms after receiving a bailout, which cannot be explained by firm heterogeneity.

Selection Bias

In this section I apply propensity score matching in order to address potential concerns of selection bias. The objective of this matching procedure is to make bailout and non-bailout banks comparable across observable variables. The matching exercise mimics a natural experiment in which treatment and control group are similar on bank level observables, such as capitalization or size, but differ with respect to the treatment - bailouts in this case. Moreover, I now compare bailout and non-bailout banks that are similarly affected by the banking crisis itself, which provides an alternative way to address bank heterogeneity discussed in Section 2. To implement propensity score matching I proceed in three steps. First, I implement the kernel weighting density algorithm. Second,

Figure 1: **Propensity Score Distribution**



Note: This Figure depicts the propensity score distribution before and after the implementation of the kernel weighting, to assess the quality of the propensity score matching. The figure shows that before matching, bailout and non-bailout banks are heterogenous across observable variables. After matching bailout and non-bailout banks are now comparable across observables. For further details on observable variables and the matching procedure see Section 3.2.

I assess the quality of the match. Third, I will repeat the regression of Equation (5) on the matched sample.

I implement propensity score matching using the kernel weighting density algorithm on following observable variables: home country, year, total assets, leverage, tier 1 capital ratio, liquidity risk, non-performing loans, return on assets, globalness (defined as number of active borrower countries on the syndicated loan market) and political connections (defined as dummy with value one if the home government has a positive ownership share in the bank).

To assess the quality of the match, Figure 1 depicts the propensity score distribution before and after the implementation of the kernel weighting. The figure shows that before matching, bailout and non-bailout banks are heterogeneous across observable variables. However, the propensity score distribution of bailout and non-bailout banks looks similar after the match. This suggests that, after implementing the match, bailout and non-bailout banks are now comparable across observables and only differ in terms of the bailout treatment.

We can now proceed to the analysis of the treatment effect by repeating the regression exercise of section 3.1 on the matched sample. Treatment and control group are now matched in terms of observable variables; and differ only in terms of whether they receive a bailout or not. Table 9 shows that regression results on the matched sample are similar to the previous results without matching. Coefficients remain comparable both in terms of statistical significance and economic magnitude. Intuitively, two banks that are now similar in terms of a number of observable variables, such as capitalization or profitability, but differ in whether they receive a bailout, change their home bias differentially. The bank affected by a bailout increase its home bias substantially more than the unaffected bank. This suggests, that the results discussed in Section 3.1 are unlikely driven by a selection bias.

TABLE 9: **Matching: Effect of Bailouts on Home Bias in Lending**

VARIABLES	(1) Bias	(2) Bias	(3) Bias	(4) Bias
Home × Bailout	0.204**	0.209**	0.234***	0.209***
	(0.0845)	(0.0817)	(0.0832)	(0.0776)
Home	0.617***	0.611***	0.835***	0.838***
	(0.0583)	(0.0522)	(0.0530)	(0.0623)
Bailout	-0.0291	-0.0358	-0.0147	-0.0344*
	(0.0244)	(0.0218)	(0.0251)	(0.0207)
Assets	-0.00712	0.0648	0.0225	0.0492
	(0.0308)	(0.0421)	(0.0307)	(0.0455)
Leverage	-0.0187	0.0667	-0.228	-0.289
	(0.577)	(0.460)	(0.486)	(0.343)
Capital ratio	-0.00398***	-0.00194	0.000715	0.00127
	(0.00142)	(0.00141)	(0.00140)	(0.00130)
NPL share	-0.198	-0.0550	0.0487	0.158
	(0.186)	(0.102)	(0.175)	(0.106)
Liquidty Risk	0.00233	0.0248**	0.000584	0.0222**
	(0.00501)	(0.0108)	(0.00421)	(0.0106)
Pol. Connect. = o,	-	-	-	-
Globalness	0.000423	0.000849	-0.00436**	-0.00473**
	(0.00190)	(0.00192)	(0.00217)	(0.00213)
Observations	19,884	19,758	19,692	19,562
PS Matching	No	Yes	No	Yes
Bank FE	Yes	Yes	Yes	Yes
Borrower country x Time FE	No	No	Yes	Yes
Cluster	Bank	Bank	Bank	Bank

Note: This table shows regressions on the bank-borrower country-year level, after implementing propensity score matching. The dependent variable is lending bias of bank b to country j at year t as defined in Section 2. $Home_{b,j}$ is a dummy with value one for the banks home country. *Bailout* is a time-varying dummy with value one during active bank bailouts as defined in Section 2. $Leverage_{b,t-1}$ is bank b's leverage in year $t-1$. $Tier\ 1\ ratio_{b,t-1}$ is bank b's tier 1 capital ratio in year $t-1$. $Liquidity\ risk_{b,t-1}$ is the ratio of total loans to deposits plus short-term liability claims, lagged by one year. $Non\text{-}performing\ loans_{b,t-1}$ is the ratio of non-performing loans (NPL) to total loans (including syndicated and non-syndicated lending), lagged by one year. $Globalness_{b,t-1}$ is defined as bank b's number of active borrower countries on the syndicated loan market in year $t-1$. For further details on the variables see Table 3. All standard errors are clustered both at the bank and year level. *** p<0.01, ** p<0.05, * p<0.1

Geographic Diversification and Industry Specialization

It may be that bailouts are driven by banks business models giving rise to a potential source of omitted variable bias. For instance, findings in Doerr and Schaz (2019) show that bank lending during banking crises is more stable for banks with a higher geographic diversification of their international loan portfolio. Moreover, Boskovic, Doerr and Schaz (2019) present evidence that banks stabilize lending to firms in their specialized industry during crises. As governments will likely take the ex-post lending performance of the banks into account when deciding on a bank rescue, it could be that bailouts are driven by banks' geographic diversification or industry specialization.

Table 10 tests whether banks' geographic diversification or industry specialization increase the likelihood of banks to receive a bailout. Results show that neither industry specialization nor geographic diversification of banks are associated with a higher bailout probability of banks. This result holds across different specifications, using both simple OLS and saturated fixed effects models. These findings suggest that bailouts are unlikely to be affected by either banks' geographic diversification or banks industry specialization mitigating concerns on omitted variable bias arising from banks business models.

Table 10: **Effect of Banks' Geographic Diversification and Industry Specialization on Bailout Probability**

VARIABLES	(1) Bailout	(2) Bailout	(3) Bailout	(4) Bailout	(5) Bailout
Industry spec.	-0.001	0.035	0.005	0.058	0.058
	(0.041)	(0.047)	(0.045)	(0.052)	(0.052)
Geogr. diversification	0.047	-0.110	0.048	-0.116	-0.116
	(0.042)	(0.123)	(0.083)	(0.108)	(0.109)
Assets	-0.010*	-0.040	-0.012	-0.182**	-0.182**
	(0.006)	(0.064)	(0.010)	(0.080)	(0.081)
Leverage	1.894***	0.308	1.646**	-0.503	-0.503
	(0.328)	(0.816)	(0.741)	(0.735)	(0.742)
Capital ratio	0.007***	0.010*	0.004	0.001	0.001
	(0.002)	(0.006)	(0.004)	(0.004)	(0.004)
NPL share	1.297***	0.856**	1.102***	0.555*	0.555*
	(0.124)	(0.294)	(0.328)	(0.299)	(0.302)
Interest rate home	0.000**	0.000	0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Liquidty Risk	0.001	0.003	0.003	0.005	0.005
	(0.007)	(0.004)	(0.005)	(0.004)	(0.004)
Globalness	0.003***	-0.000	0.003**	0.002	0.002
	(0.001)	(0.005)	(0.001)	(0.005)	(0.005)
Constant	-1.734***				
	(0.308)				
Observations	1,228	1,201	1,228	1,201	1,201
R-squared	0.180	0.701	0.205	0.734	0.734
Bank FE	No	Yes	No	Yes	Yes
Time FE	No	No	Yes	Yes	Yes
Country FE	No	No	No	No	Yes
Cluster	Bank + Time	Bank + Time	Bank + Time	Bank + Time	Bank + Time

Note: This table shows regressions on the bank-year level using a linear probability model. The dependent variable is $Bailout_{b,t}$, a time-varying dummy with value one during active bank bailouts as defined in Section 2. $Industry\ specialization_{b,t}$ is measured as the ratio of loans granted by bank b to all borrowers of industry i in time period t relative to bank b's total lending granted in the same period, as defined in Boskovic, Doerr and Schaz (2019). $Geographic\ diversification_{b,t}$ is defined as banks loan portfolio diversification across borrower countries as in Doerr and Schaz (2019). $Leverage_{b,t}$ is bank b's leverage. $Tier\ 1\ ratio_{b,t}$ is bank b's tier 1 capital ratio. $Liquidity\ risk_{b,t}$ is the ratio of total loans to deposits plus short-term liability claims. $Non\text{-}performing\ loans_{b,t}$ is the ratio of non-performing loans (NPL) to total loans (including syndicated and non-syndicated lending). $Interest\ Rate\ Home_{b,t}$ defines the average outstanding interest rate to home borrowers on the syndicated loan market. $Globalness_{b,t}$ is defined as bank b's number of active borrower countries on the syndicated loan market in year t. For further details on the variables see Table 1. All standard errors are clustered both at the bank and year level. *** p<0.01, ** p<0.05, * p<0.1

4 Real Effects

To examine whether the negative loan supply to foreign firms has real effects, I will now turn to the firm-year level. So far, bank-borrower country level regressions capture changes in lending by a bank to all borrowers from a specific country. However, if firms are able to switch banks or use alternative forms of funding, such as issuing corporate bonds, changes in bank lending may not affect firm performance. Suppose a bailout bank cuts lending to a foreign firm. If this firm then forms a new borrowing relationship with a bailout bank at home, or issue a corporate bond, this will mitigate the negative loan supply effect. To establish a link between the negative loan supply shock and real effects I test for credit substitution by firms in two steps. I analyze firm's credit substitution, first, by switching banks on the syndicated loan market and, second, by issuing alternative debt instruments. I find that firms with stronger relationships with foreign bailout banks experience a larger drop in lending, which cannot be undone by credit substitution. This imperfect credit substitution gives rise to real effects: Firms with stronger reliance on foreign bailout banks perform worse.

4.1 Credit Substitution on the Syndicated Loan Market

I now analyze the impact of bailouts on firm lending and test for credit substitution on the syndicated loan market. Table 11 shows results of estimating regression Equation (6) and addresses firm heterogeneity through different combinations of fixed effects and firm controls. Column (1) controls for unobservable time-invariant firm characteristics through firm fixed effects and time-varying unobservable firm characteristics through country*industry*year fixed effects. The dependent variable is loan growth (Δ *loan volume*$_{f,t}$). The coefficient on *foreign affected banks* is negative and statistically significant at the 1 % level. Increasing dependence on foreign affected banks from the 10^{th} to the 90^{th} percentile decreases loan growth by 6.5 % $((0.71-0.0) \times -0.092)$. The coefficient for dependence on *foreign unaffected banks* is about half in size of the coefficient for foreign affected banks. This suggests that the flight home effect documented in (Giannetti and Laeven, 2012) cannot explain the documented increase in home lending fully. Although all foreign banks are found to retrench in general in line with the flight home hypothesis, the effect for foreign bailout banks is twice as strong. In contrast, firms that have relationships with *home affected banks* do not experience an increase in lending after these banks are bailed out. Thus, firms can not undo the fall in credit by foreign bailout banks by resorting to home bailout banks. Overall, this suggests that financial protectionism leads to a negative loan supply effect on foreign firms.

TABLE 11: **Impact of Bailouts on Firm Lending**

VARIABLES	(1) Δ loan volume	(2) Δ loan volume	(3) Δ loan volume	(4) Δ loan volume
foreign affected banks	-0.092***	-0.150***	-0.091***	-0.132***
	(0.020)	(0.039)	(0.015)	(0.026)
foreign unaffected banks	-0.055***	-0.102***	-0.050***	-0.081***
	(0.017)	(0.030)	(0.013)	(0.021)
home affected banks	0.007	-0.035	-0.001	-0.021
	(0.018)	(0.061)	(0.013)	(0.035)
assets		0.041***		0.026***
		(0.010)		(0.006)
leverage		0.131***		0.116***
		(0.036)		(0.023)
sales		0.000		0.000*
		(0.000)		(0.000)
liquidity		0.031**		0.029**
		(0.015)		(0.012)
common equity		-0.000		-0.000*
		(0.000)		(0.000)
Observations	87,354	25,667	130,107	43,244
R-squared	0.360	0.377	0.163	0.171
Firm FE	Yes	Yes	Yes	Yes
Country $\times$ Time FE	-	-	Yes	Yes
Country $\times$ Industry $\times$ Time FE	Yes	Yes	-	-
Controls	-	Yes	-	Yes
Cluster	Firm	Firm	Firm	Firm

Note: This table shows regressions on the firm-year level. The dependent variable is the log difference of the loan volume of firm f received by all banks at year t; $\textit{foreign affected}_{f,t-1}$ is the share of firm f's outstanding loan volume coming from foreign banks affected by a bailout at t. $\textit{foreign unaffected}_{f,t-1}$ is the share of loans coming from banks unaffected by a bailout. $\textit{home affected}_{f,t-1}$ is the share of firm f's outstanding loan volume coming from home banks that received by a bailout at t. $\textit{assets}_{f,t-1}$, $\textit{leverage}_{f,t-1}$, $\textit{sales}_{f,t-1}$, $\textit{liquidity}_{f,t-1}$ and $\textit{common equity}_{f,t-1}$ is the respective balance sheet variable of firm f lagged by one year. For further details on the definition of variables see Section 2 and for summary statistics see Table 4. All standard errors are clustered at the firm level. *** p<0.01, ** p<0.05, * p<0.1

The results in Table 11 highlight that firms are unable to undo a fall in credit from a foreign bailout bank by switching banks on the syndicated loan market. The results are robust to alternative specifications. Effects are similar when absorbing demand effects instead with less demanding country*year fixed effects in column (3). In addition to the time-varying fixed effects, I add firm-year controls to control for loan demand, restricting the sample to firms for which I have balance sheet information in column (2) and (4). The coefficient on foreign affected banks remains stronger than for foreign unaffected banks, although the difference now becomes slightly smaller, suggesting that controlling for firm demand is important but that the story cannot be explained by firm heterogeneity only. The result on imperfect credit substitution of firms is a common finding in the literature on banking crises (Smith, Ongena and Smith, 2016; Cohen and Pascaline, 1997).

To disentangle financial protectionism from the idiosyncratic bank shock that are both related to the bailout in the first place, I will compare foreign affected with the control group home affected. Intuitively, both capture the exposure to banks that are bailed out and are thus all subject to idiosyncratic bank shocks. The difference between these two groups is now only the nationality of the borrower relative to the nationality of the bailout bank. Table 11 illustrates that while exposure to foreign affected banks has a negative effect on a firm's loan growth, exposure to home affected banks has no effect irrespective of the specification. This shows that while banks cut lending to foreign firms they do not extend more loans to home firms following a bailout.

Overall, this documents a differential effect of bank bailouts on lending to firms, depending on the relative nationality between firm and bank. These results provide evidence that banks engage in financial protectionism, that cannot be explained by idiosyncratic bank shocks and the flight home effect documented in the literature.

4.2 Credit Substitution into Alternative Debt Instruments and Firm Performance

I now analyze the ability of firms to use alternative debt instruments and the impact of bailouts on firm performance. To obtain data on the liability side of firms, I now restrict the sample to firms with available balance sheet information. Table 12 shows results of estimating regression Equation (6) using the growth rates of long-term debt, employment and sales as dependent variables. In order to absorb loan demand, I add firm controls, firm fixed effects as well as country*industry*year fixed effects to all specifications. Column (1) shows that firms can at most imperfectly substitute the decline in syndicated lending by alternative sources of funding - including non-syndicated loans and corporate bonds. Consistent with the fall in credit, I find that firms borrowing from foreign affected banks perform worse than firms borrowing from foreign unaffected banks and home affected banks. Moving firms from the 10^{th} to the 90^{th} percentile in terms of dependence on foreign affected banks, leads to lower long-term debt (-6.7 %, column (1)), sales (-3.5 %, column (2)) and employment growth (-3.0 %, column (3)). The real effects of foreign unaffected banks are around three-quarters in size. Therefore, the difference in performance between firms relying on foreign affected and foreign unaffected banks is less pronounced when looking at real effects, compared to the nominal lending effects.

TABLE 12: **Impact of Bailouts on Credit Substitution and Firm Performance**

	(1)	(2)	(3)
VARIABLES	Δ long-term debt	Δ sales	Δ employment
foreign affected banks	-0.094**	-0.049***	-0.043***
	(0.042)	(0.015)	(0.014)
foreign unaffected banks	-0.075**	-0.035***	-0.036***
	(0.031)	(0.012)	(0.011)
home affected banks	0.020	0.048	-0.006
	(0.112)	(0.030)	(0.033)
assets	0.250***	0.078***	0.052***
	(0.016)	(0.006)	(0.005)
leverage	1.268***	-0.022	0.011
	(0.060)	(0.019)	(0.017)
sales	-0.000	0.000***	-0.000
	(0.000)	(0.000)	(0.000)
liquidity	0.317***	0.071	0.057***
	(0.050)	(0.046)	(0.021)
common equity	-0.000**	-0.000***	0.000
	(0.000)	(0.000)	(0.000)
Observations	24,568	25,531	22,170
R-squared	0.463	0.618	0.512
Firm FE	Yes	Yes	Yes
Country × Industry × Time FE	Yes	Yes	Yes
Cluster	Firm	Firm	Firm

Note: This table shows regressions on the firm-year level. The dependent variables Δ*long-term debt*$_{f,t}$, Δ*sales*$_{f,t}$ and Δ*employment*$_{f,t}$ are the log difference of firm f's long-term debt, sales and employment respectively. *foreign affected*$_{f,t-1}$ is the share of firm f's outstanding loan volume coming from foreign banks affected by a bailout at t. *foreign unaffected*$_{f,t-1}$ is the share of loans coming from banks unaffected by a bailout. *home affected*$_{f,t-1}$ is the share of firm f's outstanding loan volume coming from home banks that received by a bailout at t. *assets*$_{f,t-1}$, *leverage*$_{f,t-1}$, *sales*$_{f,t-1}$, *liquidity*$_{f,t-1}$ and *common equity*$_{f,t-1}$ is the respective balance sheet variable of firm f lagged by one year. For further details on the definition of variables see Section 2 and for summary statistics see Table 4. All standard errors are clustered at the firm level. *** p<0.01, ** p<0.05, * p<0.1

In sum, Tables 11 and 12 suggest that the foreign syndicated lending contraction has real economic effects on the affected firms. As banks engage in financial protectionism they cut lending to foreign firms. In turn, these firms cannot undo this negative loan supply effect. Neither by switching banks on the syndicated loan market nor by using other forms of funding such as non-syndicated loans or corporate bonds. Thus, negative loan supply to foreign firms paired with imperfect credit substitution gives rise to real effects: Firms that depend more on foreign bailout banks experience lower loan, sales and employment growth.

5 Credit Allocation

In this section, I examine whether bailouts distort credit allocation in the home market. If government intervention shifted credit allocation towards larger, safer and less innovative firms, this would lower productivity and growth in the home market. To test the effect on credit allocation, I sort borrowers into the bottom and top halves according to their distribution of size, R&D intensity and ROA volatility, fixing the distribution at $t-1$. Where size is defined by borrower f's total assets, R&D intensity is the ratio of R&D expenditure over sales, and ROA volatility is an ex-ante volatility measure defined as the five-year standard deviation of firm f's return on assets (ROA, using profit & loss before tax) from year $t-5$ to $t-1$, following Heider et al. (2019). Within borrower types, I then compare lending, holding the same borrower constant.

Table 13 examines the shift in credit allocation in the home market distinguishing borrowers by size, risk and R&D intensity. Comparing effects at home and abroad, bailout banks increase lending within large borrowers, while they do not increase lending to small borrowers (columns 1 and 2). In columns 3 and 4, I instead split borrowers into the top and bottom halves according to the distribution of R&D intensity. Within less innovative borrowers, bailout banks increase their lending more at home than abroad. Within more innovative borrowers, this coefficient is positive but of lower magnitude. Moreover, comparing effects at home relative to abroad, bailout banks increase their loan volume within safe borrowers, while they do not increase lending within risky borrowers (if anything, they decrease lending, columns 5 and 6).

In sum, these results provide evidence that government intervention distorts the credit allocation in the home market by protecting larger, safer and less innovative firms, which could be harmful for the outlook of growth and productivity in the home market.

TABLE 13: **Impact of Bailouts on Banks' Loan Portfolio**

VARIABLES	(1) Bottom-half firm size	(2) Top-half firm size	(3) Bottom-half R&D intensity	(4) Top-half R&D intensity	(5) Bottom-half RoA volatility	(6) Top-half RoA volatility
Home × Bailout	0.010	0.069*	0.137***	0.100**	0.066**	-0.049
	(0.027)	(0.035)	(0.043)	(0.046)	(0.028)	(0.036)
Observations	57,339	62,493	21,531	22,371	56,421	54,678
Bank × Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank × Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm × Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Cluster	Country × Time	Country × Time	Country × Time	Country × Time	Country × Time	Country × Time

Note: This table shows regressions on the bank-firm-year level. The dependent variable is the log outstanding loan volume of bank b to borrowers f at year t; The sample is split into the top and bottom half of the annual median according to the distribution of firm size, firm R&D intensity and firm RoA volatility; *Home* is a dummy with value one for the banks home country; *Bailout* is a time-varying dummy with value one during active bank bailouts as defined in Section 2. For further details on the variables see Table 5. All standard errors are clustered both at the country-year level. *** p<0.01, ** p<0.05, * p<0.1

6 Mechanism

This section provides evidence that governments engage in financial protectionism and that the mechanism operates through a transfer of control rights from bank to government. In particular, governments gain novel influence over a bank through a nationalization that accompanies the bailout of the bank. In turn, the government gains influence over the business model as part of the bailout and, thus, suades the bank to prefer home borrowers in their lending. In contrast, bailout banks that only receive a recapitalization but are not nationalized, and hence no transfer of control rights to the government occurs, do not significantly change their loan mix.

The propensity of banks to prefer home over foreign borrowers is strongest in those cases, where a transfer of control rights occurs for those banks that have no political connections before the bailout. In those cases governments gain novel influence over a bank to which it had no political connections, in the form of public ownership, before the bailout. Thus, financial protectionism is strongest in those cases where bailouts brought about a new increase in government control over a particular bank.[20]

To test the mechanism that operates through an increase in governments' control rights, I capture following two dimensions. First, whether the government already has influence over the bank irrespective of the bailout. I distinguish banks into banks with

[20]The importance of political connections for bank bailouts has been shown in Duchin and Sosyura (2012); Chavaz (2016), while Bertrand, Kramarz, Schoar and Thesmar (2018); Goldman, Rocholl and So (2013) highlight importance of political connections more generally.

TABLE 14: **Transfer of Control Rights and Political Connections**

VARIABLES	(1) log loan volume	(2) Bias
Home × Control Rights × No Political Connection	2.538***	0.589*
	(0.750)	(0.295)
Home × Control Rights	-0.156	0.142
	(0.673)	(0.193)
Home × No Control Rights × No Political Connection	0.325	0.0972
	(0.450)	(0.157)
Home × No Control Rights	0.361	0.152
	(0.389)	(0.119)
Home × No Political Connection	0.0654	0.0433
	(0.231)	(0.0818)
Home	2.013***	0.678***
	(0.187)	(0.0661)
Observations	48,539	47,850
Bank x Time FE	Yes	Yes
Borrower country x Time FE	Yes	Yes
Cluster	Bank + Time	Bank + Time

Note: This table shows regressions on the bank-borrower country-year level. In column 1, the dependent variable is the log outstanding loan volume of bank b to borrowers in country j at year t; In column 2, the dependent variable is lending bias of bank b to country j at year t as defined in Section 2; *Home* is a dummy with value one for the banks home country. *Control Rights Transfer*$_{b,t}$ is a dummy with value one if the bailout of bank b is a nationalization. *Political Connections*$_{b,t}$ is a dummy with value one if the home government has a positive ownership share in bank b. For further details on the variables see Table 3. All standard errors are clustered both at the bank and year level. *** p<0.01, ** p<0.05, * p<0.1

and without political connections to capture the extent to which the government already has influence over the bank before the bailout. A bank is defined as politically connected, if either the home government is one of its shareholders or if the institution is publicly owned. Second, whether a bailout comes with a transfer of control rights from bank to the government. I distinguish bailouts into two categories: i) bailouts that come with a transfer of control rights and ii) bailouts that come without a transfer of control rights to the government. I define a bailout with a transfer of control rights to the government as a bank nationalization as this gives the government direct influence over the banks' management. A bailout with no transfer of control rights is defined as a pure capital injection, either through a recapitalization or by providing unusual liquidity, but without a change in public ownership of the bank.[21]

Table 14 provides evidence in support of the mechanism that works through a transfer

[21] I omit bank-borrower country fixed effects as both *Political Connections* and *Home* are invariant at the bank-borrower country level.

of control rights to the government. Column 1 tests the differential effect of a transfer of control rights for politically unconnected banks on lending through triple interactions. The strongest increase in home lending is associated with bailouts that transfer control rights from ex-ante politically unconnected banks to the government. As can be seen in row three, no significant effect on home lending can be found for those bailouts that do not transfer control rights from politically unconnected banks to the government. I do not find evidence for protectionism operating through bailouts without transfer of control rights (i.e. pure capital injections) independent of a banks' political connections.

Overall, these findings suggests that financial protectionism operates through a transfer of control rights from ex-ante politically unconnected banks to the government, as the government establishes direct influence over the banks' business through the bailout. In turn, governments make use of their newly gained control rights by persuading the respective bank to redirect lending towards the home market in return for the bailout - in line with the financial protectionism hypothesis (Rose and Wieladek, 2014).

7 Conclusion

When governments support their ailing banking sector, they have an incentive that the home economy benefits from this controversial measure. This paper provides evidence that governments engage in financial protectionism by persuading banks to redirect loan supply towards the home market in return for the bailout. In particular, I find that bailout banks change their loan mix in favor of home borrowers, while this is not the case for non-bailout banks. I document that the mechanism of financial protectionism operates through a transfer of control rights from government to bank. Additionally, financial protectionism alters the structure of cross-border banking and thereby affects the real economy. In the home market, government support for banks distorts credit allocation towards larger, safer and less innovative firms. Abroad, financial protectionism leads to a negative loan supply shock to foreign firms that translates into lower sales and employment growth due to imperfect credit substitution.

This paper contributes to the debate on designing the international architecture of bank resolution within the European Banking Union. I provide evidence that bank support located at the national government level discourages international economic activity, reduces financial integration, distorts credit towards less productive firms and harms both growth and employment.

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Selbständigkeitserklärung

Ich bezeuge durch meine Unterschrift, dass meine Angaben über die bei der Abfassung meiner Dissertation benutzten Hilfsmittel, über die mir zuteil gewordene Hilfe sowie über frühere Begutachtungen meiner Dissertation in jeder Hinsicht der Wahrheit entsprechen.

Berlin, 20. Februar 2019

Philipp Schaz